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Examining Faculty Autonomous And Controlled Motivation For Learning Analytics

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EXAMINING FACULTY AUTONOMOUS AND CONTROLLED MOTIVATION FOR LEARNING ANALYTICS

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Michael James Herbert

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“The essence of the independent mind lies not in what it thinks, but how it thinks.”

-Christopher Hitchens

ABSTRACT

Learning Analytics (LA) is the collection and analysis of data about learners and their environments. University faculty are among some of the most important stakeholders in the successful implementation of LA initiatives, whose participation can influence the success or failure of innovative educational changes. However, limited research exists surrounding university faculty members' perceptions and motivation to adopt LA practices in their courses. The purpose of this study was to examine faculty institutional trust, course data control, and motivation for LA practices in their courses. Examining survey data from 250 university faculty, this quantitative study employed structural equation modeling to analyze Self-Determination Theory measures of faculty motivation for LA utilization in their courses. The study also analyzed measures of institutional trust and course data control as they relate to faculty basic psychological needs for LA. Analysis of a hypothesized and post-hoc model found that faculty perceptions of institutional trust, course data control, motivation, and regulation types predicted faculty members' utilization of LA in their courses. Specifically, amotivation, or a lack of incentive or value for LA practices, was the strongest negative predictor and mediator of faculty members' utilization of LA in their courses. The results of this study provide implications for understanding faculty motivation and engagement for LA initiatives and practices in institutions of higher education. Moreover, the results of this study highlight a prevailing necessity to better understand faculty members' sense of awareness, application, and value of LA in their courses as rapid technology advancements become more prevalent in higher education. This is one of the first studies to utilize structural equation modeling to better understand the role of motivation in university faculty members' perceptions and utilization of LA in their courses.

CHAPTER I

INTRODUCTION

Technology adoption in higher education is not a new phenomenon, and in many ways higher education institutions in the United States have been at the forefront of such initiatives going back to the middle of the 20th century (Picciano, 2012). With the first offering of online undergraduate courses in 1985 (Harasim, 2000), technology adoption quickly transitioned into expanded curricular options of universities with the internet boom of the 1990s and early 2000s. This trend informed numerous studies related to technology utilization by higher education institutions and faculty, examples being the effects of learning management systems (LMS) on university teaching and learning (Coates et al., 2005), along with student retention in online courses (Herbert, 2006).

Over time, institutions of higher education began to accrue vast amounts of data, similar to the practices of corporations, where they began integrating this data into their business models to inform more data driven decision-making (Attaran et al., 2018). By the early 2000s higher education institutions began to dedicate further attention to analytics and data-driven decision making (Siemens, 2013). With the growing amount of student data being collected in LMS', the field of Learning Analytics (LA) was established in part to utilize the vast amount of data to inform positive student learning outcomes and improve learning environments. In Fiaidhi's (2014) article on the next steps for learning analytics they posited that learning analytics is the third wave of development in instructional technology; whereas the growth and integration of LMS platforms in educational institutions was the second wave, preceded by the adoption of Web 2.0 or social networks.

Learning Analytics

Learning analytics (LA) is a culmination of technology adoption trends and practices in higher education institutions, the establishment of LA lies within, but not limited to, business intelligence (Clow, 2013), academic analytics (Campbell et al., 2007), and predictive analytics (Gašević et al., 2016). LA eventually grew into its uniquely established field of study primarily out of educational data mining and academic analytics. The first definition of LA was established in the call for papers from the Society for Learning Analytics Research (SoLAR) First International Conference, and ultimately focused on the collection and analysis of data about learners in their environments. LA offers a series of benefits for learners, educators, and institutions of learning, which include personalized learning for students (Klašnja-Milićević et al., 2020), improved student outcomes (Lu et al., 2017), improved curriculum design (Reyes, 2015), improved instructor development (Avella et al., 2016), and increased student retention (Pradeep et al., 2015).

Even though there are a series of proposed benefits that LA can provide, a prevailing number of challenges remain. This includes an increasing pressure to investigate claims of improved student learning outcomes as the result of LA utilization (Viberg et al., 2018), limited research concerning agents outside of the student population (i.e., faculty, staff, institutions; Clow et al., 2016), insufficient training opportunities (Norris & Baer, 2013), and a call for additional empirical backing for the posited benefits of LA among various stakeholder groups (Newland et al., 2015; Tsai & Gasevic, 2017). Worth mentioning as well is the growing concern surrounding ethics, privacy, and legality in the collection and utilization of LA data in institutions of higher education (Pardo & Siemens, 2014; Prinsloo & Slade, 2019). While LA is a relatively new field of practice and research, with a growing number of articles addressing its benefits and challenges, a limited understanding remains concerning university faculty member's perceptions and motivation to utilize LA practices in their courses.

Faculty Motivation

In recent years, a growing line of research has focused on the motivation of university faculty members to address critical gaps of understanding behavior related to teaching and research, as well as by engaging with concerning trends regarding publications and research output in the United States (Boroush, 2020; Litwin, 2014). Moreover, current trends concerning graduate student perceptions of the academic job market and the gradual shift of PhD graduates to private industry also raises questions concerning the future of the American professoriate (Woolston, 2022). Traditionally, research on university faculty members has concentrated on external factors including socio-environmental and institutional characteristics (Daumiller et al., 2020), with a considerably limited number of studies focused on motivation. There are a variety of reasons for why this is such an underdeveloped area of research, including demotivating factors of rejection in publishing research (Minter, 2009), and logistical reasonings of sample diversity and limited participation based on faculty being overburdened by contractual obligations of teaching, research, and service (Catano et al., 2010; Winefield et al., 2008).

Over time, there have been a variety of motivational and emotional theories applied to research concerning university faculty. These include Bandura's (1997) Self-Efficacy Beliefs theory, central of which is the belief of individuals as to whether they are able to engage with a specific task successfully. This theory has been applied to better understand faculty members emotions and teaching styles (Zhang et al., 2017), as well as in the task of conducting research (Forester et al., 2004). Another theoretical approach includes Pekrun's (2006) Control-Value Theory of Achievement Emotions, which emphasizes the role of emotions of achievement in the academic setting. Control-value theory has been utilized to better understand the role of emotions in predicting teaching and research performance (Stupnisky et al., 2019), where emotions were a significant factor in perceived teaching and research success. This leads to another critical theory applied to the field of faculty motivation research, Deci and Ryan's (1985) Self-Determination Theory.

Self-Determination Theory

Deci and Ryan's Self-Determination Theory (SDT) has received considerable empirical support from a variety of fields including banking (Hussain et al., 2015), K-12 education (Reeve & Halusic, 2009), and higher education (Jeno et al., 2018). SDT is a theory of human behavior that emphasizes psychological measures of human motivation. Specifically, SDT focuses on inherent human capacities for engagement and wellness in a variety of activities and domains. SDT is especially important in the development of psychological measures and causal models of human behavior to understand what factors influence an individual's ability to engage in specific tasks. The foundation of SDT is *autonomy*, or the sense to behave with willingness or fully endorse in a behavior or activity an individual is engaged with. Additionally, SDT posits that three basic psychological needs are critical for optimal functioning and integration. The three basic psychological needs are *autonomy*, which is a sense of freedom to engage with activities, *competency*, where an individual feels prepared or experienced to engage with a task successfully, and *relatedness*, engaging in a behavior or task to feel a sense of closeness or relatability with others (Deci & Ryan, 2012).

The combination of these three basic psychological needs influence an individual's sense of *autonomous motivation* to engage with an activity based on enjoyment or self-identified importance in doing so. Additionally, SDT frames human motivation in self-determined and non-self-determined regulations. Self-determined motivation is comprised of *intrinsic motivation*, an activity or behavior driven by enjoyment or genuine interest, and *identified regulation*, the engagement in a task or behavior based on its perceived value or importance. Conversely, non-self-determined motivation is composed of *external* or *extrinsic regulation*, where an individual's behavior or engagement in an activity is influenced by outside factors. These include *introjected regulations*, both positive and negative, where an individual performs an activity based on avoidance of guilt or anxiety, as well as *external regulation*, performance for reward or avoidance of punishment. On the opposite end of the spectrum is *amotivation*, where individuals are uncertain of the value, benefit, or reasoning behind engaging in an activity or behavior.

When applied to faculty motivation, SDT has been employed to discover the significance of intrinsic motivation in online teaching (Cook et al., 2009), and its power as a predictor of perceived teaching success (Stupnisky et al., 2017). Additionally, Stupnisky et al. (2018) found that the satisfaction of SDT basic psychological needs during teaching predicted greater autonomous motivation for teaching. Similarly, Stupnisky et al. (2019a) found that autonomous motivation for research was critical in perceived research success.

Faculty Motivation, Perceptions, and Utilization of Learning Analytics

Research on faculty motivation in the area of LA is especially limited, moreover when approached through the lens of SDT. Within the context of this study, SDT is hypothesized as an appropriate theoretical approach to address challenges inherent within LA as a field of research. This approach is a critical addition to the limited empirical understanding of why university faculty members would choose to utilize LA practices in their courses, and their general perceptions of LA as factors which could influence or predict their motivation to engage with it in practice. While there are a variety of theories and frameworks proposed within LA including the Learning Analytics Readiness Instrument (LARI; Arnold et al., 2014) and Davis' (1989) Technology Acceptance Model (TAM), motivational theories may be a key lens to better understand how faculty perceive and utilize LA. SDT has also been utilized to understand technology acceptance and student engagement with LA practices (Ameloot & Schellens, 2018; Sergis et al., 2018).

When concentrating on faculty members' motivation for LA, research is very limited, but garnering more attention in recent years. This is concerning for a variety of reasons, but more so for the fact that faculty play such a critical role in LA initiatives and adoptions of practice in their courses (Furco & Moely, 2012; Rehrey et al., 2019). Over time, most of LA motivation research has focused on student perspectives, such as how LA can influence student motivation (Aguilar et al., 2021; Karaoglan et al., 2021; Lonn et al., 2015). To date, only one other study has focused on the role of SDT in faculty motivation for LA in a quantitative methodology, where Amida et al. (2022) utilized SDT and Eccles' Expectancy-Value Theory to understand faculty member's utilization of LA tools in their courses.

Research surrounding faculty perceptions and utilization of LA has been sporadic throughout the establishment of LA as an independent field, where many of the existing studies had previously focused on technology adoption and teaching (Mitra et al., 1999; Spotts and Bowman, 1995), as well as the adoption of the newly developed Web 2.0 technology of the late 1990s and early 2000s (Ajjan & Harthshorne, 2008). While many previous studies have looked at faculty interaction and utilization of technology, it is worth noting that early perceptions among faculty towards areas that would comprise the field of LA indicated early observations of skepticism, especially towards academic analytics (Campbell et al., 2007; Parry, 2012). Eventually, this line of research would lead to additional studies that centered on LA as a predictor of student success while factoring in faculty perspectives (Dietz-Uhler & Hurn, 2013), concerns surrounding LA that included faculty perspectives (Dringus, 2012), and faculty perceptions and adoption of course data (Svinicki et al., 2016).

Research centered upon faculty utilization of LA is also growing, including studies by Khan et al. (2017) which incorporated faculty perspectives of LA, Bollenback and Glassman's (2018) study which looked at the rank of faculty members in how it influenced LA adoption in their courses, and Rehrey et al.'s (2019) study determining the effectiveness of an LA program to engage faculty. More recently, Arthars and Liu (2020) conducted a qualitative study which highlighted the importance of faculty in the adoption and success of LA platforms. Throughout these studies that incorporate the perceptions and utilization of LA by faculty members, a variety of similar themes emerged that have informed the basis of the current study.

Faculty Trust and Course Data

LA research focused on faculty member's trust is another limited area but has been suggested throughout assorted studies as an important factor in the perceptions and utilization of LA. Specifically, trust is an important component in the adoption and growth of LA initiatives (Pardo & Siemens, 2014). Research addressing faculty members' general sense of trust has been previously established but contains a limited number of studies which include Shoho and Smith's (2004) study of trust in the faculty population as potentially impacting the success of students and institutional health. Additionally, Hoy and Tschannen-Moran (1999) conducted a study in an attempt to define trust in the collegiate setting, especially among colleagues and varying institutional stakeholders such as deans and students.

This study examined the role of trust in faculty members' motivation for LA utilization, continuing the work of a recent study by Alzahrani et al. (2023) which looked at the role of trust in LA adoption among teaching staff. Alzahrani et al.'s study acts as a continuation of research by Klein et al. (2019) and Tsai et al. (2021) which identify trust as critical for LA tool utilization. This study notes that while a considerably neglected area of research in LA, trust is a reoccurring theme in understanding the perceptions of faculty members towards LA initiatives, and has often been siloed into different stakeholder groups, primarily with students (Mutimukwe et al., 2022). Among the results of this study, were that data ownership was another concern as it relates to faculty members' trust.

Faculty Control of Course Data

In a prevailing theme, literature surrounding faculty control or ownership of course data is another limited area of research. Moreover, within the context of higher education ownership or control of course data is often associated with trust in an institution (Mutimukwe, 2022; Pardo & Siemens, 2014). Issues of course data control from a faculty and student perspective have often been associated with intellectual property issues, trademark issues, or copyrights of course materials (Dennen, 2016; Greenhow & Gleason, 2015). In a review of literature, it does not appear that any studies thus far have empirically looked at a faculty member's sense of ownership or control over their course data, moreover in how it influences their perceptions and utilization of LA practices in their courses. The basis for this additional study component is more so informed by general societal concerns surrounding data privacy and data ownership, where Auxier et al. (2019) and the Pew Research Center found that a majority of Americans report having little control over data collected by companies or government agencies.

This study component was also informed by a reoccurring theme throughout LA research, while not directly dealing with a faculty member's sense of control, is a common point of discussion in areas of ethics and privacy concerns, as well as data ownership. While focused on students, Tsai et al. (2020) notes that losing control over data which is shared with external entities, or the perceived risk of losing control, influences the offering of data to be used for LA practices. This feeds into a combined area of concern regarding both institutional trust and sense of control as it pertains to course data. Specifically, an apprehension with university faculty in the potential for course data and LA practices to be utilized as a component of performance evaluation. Moreover, while Tsai et al. (2020) highlighted student concerns of data control, Bollenback and Glassman's (2018) study found that faculty displayed concerns about the utilization of LA data for external purposes, with the risk of identifying faculty as potentially "bad."

Purpose of Study

The purpose of this dissertation was to examine faculty motivation for learning analytics while introducing perceived sense of control and trust with course data to predict faculty utilization of learning analytics practices. Moreover, this study seeks to understand how these factors predict LA utilization in a faculty member's courses. Ultimately, the study evaluated a model of faculty perceptions of course data control, institutional trust and course data, basic psychological needs, and motivation types as predictors of LA utilization. The overarching hypothesis for this study is that faculty perceptions of control with course data and external factors affecting faculty trust in institutional utilization of course data will have a significant impact on faculty basic psychological needs and motivation to utilize LA in their courses.

Research Questions

Four research questions informed the basis of this study:

1. What are faculty members' perceptions and practices related to course data control, institutional trust with course data, and learning analytics utilization?
2. What differences exist among faculty with respect to autonomous motivation, controlled motivation, perceptions of performance evaluation, and the utilization of learning analytics in their courses?
3. What are the relationships among faculty course data control, institutional trust, basic psychological needs, motivation types, and learning analytics utilization?
4. What factors predict basic psychological needs, motivation, and learning analytics utilization in faculty members' courses?

Significance of Study

This study contributes to the existing literature of learning analytics, faculty motivation, course data autonomy, and performance evaluation through LA. Ultimately, the study expands upon our limited understanding of what factors motivate university faculty to utilize LA, perceptions of LA practices/tools, and ultimately how faculty sense of course data control and potential performance evaluation relate to their utilization of LA. This study also provides a meaningful series of results for institutions of higher education, namely universities, in how faculty incorporate and utilize LA through support or training, and ultimately if LA should be a component of teaching performance evaluation. There are additional areas of significance to which this study contributes as well, including several implications for practice based on the results of this study, with one example being that institutions should make a concerted effort to increase the awareness of LA practices and initiatives at the macro level, then focusing on microlevel assessments of what meta-data or tools in a faculty member's LMS are beneficial or practical.

Definition of Terms

Learning Analytics (LA): The primary definition of LA in this study, "Learning analytics is the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs" (LAK, 2011) as established and adopted by the Society for Learning Analytics Research (SOLAR; Ferguson, 2012).

Learning Management System (LMS): Defined as "Online learning technologies for the creation, management and delivery of course material" (Turnbull et al., 2020, p. 164). These include platforms such as Blackboard Learn, Canvas, Desire to Learn (D2L), Moodle, and Google Classroom.

Educational Data Mining (EDM): Defined as "the application of data mining techniques to educational data" (Romero, 2010, p. 1), where data mining involves the processes of extracting useful and interpretable information from data.

Academic Analytics (AA): Defined as "Academic analytics combines select institutional data, statistical analysis, and predictive modeling to create intelligence upon which students, instructors, or administrators can change academic behavior" (Baepler & Murdoch, 2010, p. 3).

Self-Determination Theory (SDT): Defined as "A macro-theory of human motivation, personality development, and well-being" (Ryan, 2009).

Action Research: Defined as "Research directed toward a practical goal, usually an improvement in a particular process or system" (American Psychological Association, 2023).

Data Driven Decision-Making: Defined as “the systematic collection, analysis, and application of many forms of data from a myriad of sources in order to enhance student performance while addressing student learning needs” (Schifter et al., 2014, p. 420).

Summary

This chapter outlined the basis of the study, introducing the establishment of LA as a field of study, the increasing research on faculty motivation, and the roles of institutional trust and course data control in how they could influence faculty perceptions and engagement of LA practices in their courses. Moreover, it defined the purpose of the study in identifying the role of motivation in predicting LA utilization, and the implications it could have for faculty who teach in institutions of higher education. Subsequently, a review of literature is performed to support the basis of this study and provides various pieces of evidence to understand the importance faculty motivation for LA in a rapidly changing higher education industry.

CHAPTER II

REVIEW OF LITERATURE

The following chapter explores a literature review on faculty perceptions and utilization of learning analytics (LA) and faculty motivation through the lens of Self-Determination Theory (SDT). The chapter also focuses on explaining the benefits and challenges of LA, faculty perceptions and utilization of learning analytics, and the concepts of data control and faculty trust as it relates to technology.

Learning Analytics

Learning Analytics Defined

Learning analytics (LA) has been described as a compilation of fields and practices including business intelligence and analytics (Clow, 2013), web and action analytics (Elias, 2011), educational data mining (Siemens & Baker, 2012), academic analytics (Campbell et al., 2007), and predictive analytics (Gašević et al., 2016). It is also important to note that LA, educational data mining, and academic analytics are concepts which are closely related (Avella et al., 2016). Commonalities shared between these different fields of research all involve the collection and interpretation of data about students in educational settings to improve learning outcomes and inform institutional practice.

The formation and establishment of LA as its own field of research is associated with the call for papers from the Society for Learning Analytics Research (SoLAR) at their first International Conference on Learning Analytics and Knowledge in 2011 (Ferguson, 2012), it is also the most frequently cited definition of LA to date (Banihashem et al., 2018). SoLAR’s official definition of LA is “the measurement, collection, analysis and reporting of data about learners and their contexts, for purposes of understanding and optimizing learning and the environments in which it occurs” (LAK, 2011). Alternatively, Brown (2012) defines learning analytics as “the process of systematically collecting and analyzing large datasets from online sources for the purpose of improving learning processes” (Avella et al., 2016, p. 14). Ultimately, LA can also be summarized as translating learning data from multiple sources (e.g., academic data systems, LMS’, etc.) into new knowledge in education (Banihashem et al., 2022), which can provide students with insight and customized experiences for their learning, as well as enable educators to make evidence-based interventions for “the improvement of teaching and learning” (Banihashem et al., 2022, p. 2; Wise, 2014).

With the establishment of LA as a new field of research, a variety of theories were proposed over time to address the inclusion and impact of LA on various institutions of education. One of the first theories to provide a framework for LA resulted from the work of Greller and Drachsler (2012), which identified six critical dimensions, or fields of attention, to ensure “an appropriate exploitation of LA in an educationally beneficial way” (Greller & Drachsler, p. 43). The six critical dimensions of Greller and Drachsler’s LA framework are competencies, constraints, methods, data, objectives, and stakeholders, within each critical dimension are also a series of values such as prediction in objectives and teachers in stakeholders. Specifically, in the interests of this study, the critical dimension of stakeholders is particularly important as it involves the concept of data clients and data subjects. Data clients are ultimately the beneficiaries of the LA process at an educational institution, where teachers and administrators are positioned in a way to act upon the data. Data subjects are those who supply the data and trace data for an institution, this would include students and other constituents of an academic institution. One crucial element to understand as well is that Drachsler and Greller’s LA framework structures stakeholders in a pyramid formation, where students and teachers represent the lower levels that inform the upper levels which is made up of institutions and governing bodies. This pyramid represents an "information flow between LA stakeholders" (Greller & Drachsler, p. 46).

Another theoretical framework for LA was established by Siemen's (2013) Learning Analytics Model. Like Greller and Drachsler's (2012) LA framework, Siemen's model emphasizes that information sharing, and collaboration is a key component in a successful implementation of LA at educational institutions. Essentially, there needs to be collaboration from a bottom-up and top-down system, where at the bottom you have teachers collecting data through LMS statistics and small data accesses, and from the top down you have training offered to teachers and staff. Additionally, at the top there are more advanced tools in place, such as predictive modeling to inform teaching practice or intervene with struggling students. Siemen's (2013) Learning Analytics Model emphasizes the importance of a systematic approach where successful LA implementation involves the skills and resources of multiple individuals that are not possessed by a single individual (i.e., collaboration of multiple entities). Siemen's LA model also proposes a cycle of processes which begin with the collection and acquisition of data, where the data is stored and cleaned, datasets are integrated, analysis takes place to answer a series of educational questions, results are presented, and finally actions are taken based on the results of the analysis.

With the establishment of LA is a new field of research, and the development of theoretical frameworks, research has increased over time focusing on a multitude of segments within LA that include both technical and educational perspectives. Moreover, the increasing knowledge being generated about LA since 2011 has established a series of benefits and challenges to which LA can provide for learners, educators, and educational institutions.

Learning Analytics Benefits

Through the establishment of LA as its own field and line of research, numerous studies have focused on the benefits that LA can provide for students, teachers, faculty, administrators, and higher education institutions as a whole. Banihashem et al.'s (2018) systematic review of literature focused on the identification of benefits provided by LA. In the 247 articles obtained spanning 2011-2017, 18 were focused solely on the benefits of LA. These results were similar to a systematic review conducted by Avella et al. (2016), which obtained 112 articles and identified 16 which focused solely on the benefits of LA. In Banihashem et al.'s systematic review of LA studies, benefits of LA were broken down by stakeholder categories that included learners, teachers, institutions, researchers, course designers, and parents. This review of literature will focus on the benefits of LA for learners, educators (which will broadly include educators including k-12, student-teachers, instructors, faculty, etc.), and educational institutions.

Learning Analytics Benefits for Learners

One of the initial benefits that LA can provide for students is personalized learning and learning environments, which was already in demand around the establishment of LA as a field of study (Huang et al., 2012). Personalized learning "encourages the active involvement of learners in the learning process by improving learning experiences and outcomes" (Klašnja-Milićević et al., 2020, p. 232). One of the primary areas to enable this personalized learning for students through LA is the utilization of dashboards, where "a student dashboard is an interactive, historical, personalized, and analytics monitoring display that reflects student's learning patterns, status, performance and interactions" (Park & Jo, 2015, p. 112; Roberts et al., 2017). Ultimately, dashboards collect data from LMS platforms or other course data silos and present the data for students to assess their performance and areas of potential improvement in the course.

Another area of benefit that LA provides for students is improved learning outcomes. In a recent study by Lu et al. (2017) focused on learning outcomes in massive online open courses (MOOCS), teacher interventions informed by LA improved student learning outcomes and levels of engagement in the course when compared to interventions based on instructor observation. However, it is important to note that there is increasing pressure to investigate improved student learning outcomes further in LA. More recently in a review of 252 LA papers in higher education published between 2012 and 2018 Viberg et al. (2018) found that there has thus far been "little evidence that shows improvements in students' learning outcomes" (Viberg et al., p. 98). Viberg et al. go on to point out that the potential for LA to improve student learning outcomes is stronger, where 16% of papers emphasized the potential for improved learning outcomes, compared with the 9% that indicate some positive or negative evidence. While this does not suggest that there are no potential benefits that LA can provide for learning outcomes, it does highlight an argument for further empirical study. Notably, Viberg et al. highlight Arnold and Pistilli's (2012) study as being the only study "which strongly supports this proposition (i.e., that LA can improve learning outcomes)" (Viberg et al., 2018, pp. 103-104).

Arnold and Pistilli's (2012) study is one of the most cited articles in LA research, which focused on the development of the Purdue Course Signals program. Course Signals was developed in part to address student persistence in higher education. The development of Course Signals was informed in part by Tinto's (1993) encompassing work with student retention where institutions need to implement programs that support the welfare of students, programs should be inclusive of all students in the institutional population, and that proposed solutions must be integrated to enhance student success and integrate into the academic setting. The development of Course Signals focused on meeting this demand for academic integration in numerous ways, examples being the employment of "learner analytics to allow for the integration of real-time data on student performance and interaction with the LMS with demographic and past academic history information" (Arnold & Pistilli, 2012, p. 267), and also allowed faculty to engage with students by sending personalized information and status updates on their current performance in a course.

Course Signals is described as a student success system that integrates data collected by LMS platforms and higher education institutions to send meaningful feedback to students based on predictive modelling. The central premise behind Course Signals was to "utilize the wealth of data found at an educational institution, including the data collected by instructional tools (i.e., LMS platforms), to determine in real time which students might be at risk, partially indicated by their effort within a course" (Arnold & Pistilli, 2012, p. 267). Course Signals utilized a predictive student success algorithm which could be employed on-demand by the course instructors, and ultimately consisted of four measurement components that included performance based on percentages of points earned in a course to date, and effort which was indicated by student interaction with Blackboard. The "signals" element of Course Signals was directly linked to color indicators which could be associated with traffic signals, where based on the results of the SSA algorithm students would be presented with a series of three colors based on the aforementioned metrics. Red lights indicated a high likelihood of problems for student success within the course, yellow lights were indicative of potential problems in course success, and finally green lights demonstrated a high likelihood of student success in the course.

Results for Course Signals found that students who began the program and participated in at least one Course Signals integrated course were "retained at rates significantly higher than their peers who had no Course Signals classes but who started at Purdue during the same semester" (Arnold & Pistilli, 2012, p. 268). Moreover, students reported mostly positive overall experiences with the Course Signals program, with 58% indicating they would use it in every course if given the option. Faculty in general also indicated positive experiences with Course Signals, which initially included a sense of faculty caution about the system and the potential impact it could have on course loads. It is also important to recognize that a study from Lauría et al. (2013) utilized a similar system to Purdue Course Signals through the Open Academic Analytics Initiative (OAI) at Marist college and found that their predictive models had a "subsequent positive impact on the effectiveness of interventions on students at academic risk" (Lauría et al., 2013, p. 154). Additionally, a study from Smith et al. (2012) found that the frequency of student logins to an LMS platform, performance measured in grades, and engagement with course materials were successful predictors of overall course performance.

While there is more potential and opportunity to validate the utilization of LA in order to improve student outcomes and personalized learning, this review demonstrates some evidence to indicate that students can benefit from LA integration in their courses.

Learning Analytics Benefits for Educators

First, it is important to recognize the critical role that faculty and educators in general play in the success of LA, "the key constituency group is faculty, whose powerful voice and genuine participation often determine the success or failure of educational innovations, especially those that involved pedagogical and academic change" (Furco & Moely, 2012, p. 129). Among the benefits that LA can provide for educators is the ability to improve teaching performance and curriculum design through LA integration in instructor courses. Reyes' (2015) review of the stakeholders, benefits, and challenges in LA notes that LA can allow for a better understanding of how course data can enable teachers to "identify knowledge gaps, which might lead to positive intervention in student learning, changes to the design of curriculum or modification of teaching strategies" (Reyes, p. 77). Avella et al.'s (2016) review also notes that instructor performance is a key benefit for teachers by incorporating LA, where Mardikyan and Badur's (2011) study found that "data provides an opportunity to improve instructor development so that instructors are better prepared to work with students in a technological learning environment" (Avella et al., 2016, p. 20). Similarly, Xu and Recker (2012) found that data generated from instructor usage of technology could be used to identify areas of improvement for instructors in order to foster better instructor-student interactions and improve the learning environment.

Learning Analytics Benefits for Educational Institutions

While the potential benefits of LA are typically focused on students and educators, institutions of higher education are another stakeholder which stand to benefit from LA initiatives. Bannihashem et al. (2018) emphasizes that data is a growing critical resource in higher education institutions, and it can be used to support better student outcomes, provide evidence for why students may fail to understand concepts or skills, why students drop courses or fail to continue enrollment, and ultimately why some students fail to graduate. Additionally, Bannihashem et al. suggest additional institutional benefits which include improved accountability, evidence-based decision making, student-success modeling, and cost efficiency. In Conde and Hernández-García's (2015) overview, they note that LA can ultimately help institutional leaders with data-driven decision making, allowing for higher education institutions to “customize their recruiting actions and attract new students based on their needs and/or interests” (Conde & Hernández-García, p. 3). Additionally, Stewart (2017) posits that LA can help institutions move from speculative decision making to emphasize more data-driven approaches in course development and evidence-based outputs of student learning.

One of the first studies to address institutional adoption and utilization of LA was Arnold et al.’s (2014) study which developed the Learning Analytics Readiness Instrument (LARI) to help institutions advance successful analytics initiatives. Up to this point, the authors note that LA had been relatively well defined, but in part the purpose of the study was to address an area with limited research on institutional readiness to implement LA practices. The development of the instrument involved a survey of 35 faculty from nine institutions of higher education, and ultimately resulted in a five-factor instrument with strong Chronbach’s alpha scores.

Recently, an encompassing review of literature by Quadri and Shukor (2021) aimed to understand the benefits of LA specifically for institutions of higher education. Setting the stage, the authors note that LA is increasingly being utilized by institutions of higher education, which the authors suggest that LA was originally designed to focus on higher education institutions for specific sectors of resource management, student performance, and financial decision making (Joshi et al., 2020; Quadri & Shukor, 2021; Schumacher & Ifenthaler, 2018). In a review of 72 articles, Quadri and Shukor identified 25 that specifically shared a direct relationship with the benefits of LA for institutions of higher education. Among the benefits for higher education institutions were studies that focused on curriculum development and improvement (Armayor & Leonard, 2010; Pardo et al., 2017), improved student learning outcomes (Arnold & Pistilli, 2012; Pardo et al., 2016a), and the monitoring of student’s drop-out and retention efforts (Cambruzzi et al., 2015; Pradeep et al., 2015; Vasić et al., 2015).

Keeping in line with institutional benefits focused on student retention, Bronnimann et al. (2018) in a case study approach found that when LA was implemented in a program experiencing a high attrition of students from underrepresented groups, over time a data-driven approach created advantages for positive program changes. This is especially important in the context of higher education institutions attempting to recruit and retain more diverse student populations, where previous studies have found that algorithms, a component of LA, could enable “digital discrimination” in the classification or categorization of students which enables exclusionary practices aimed at being inclusionary (Norris & Lyon, 2003; Tsai, 2021). Overall, benefits that are specific to institutions of higher education are all-encompassing in how the benefits to faculty, staff, and students contribute to the greater health of universities by supporting faculty, improving curriculum, retaining students, and driving positive learning outcomes which includes graduation.

Learning Analytics Challenges

While there is a growing number of studies indicating strong potential benefits of LA, there are also considerable challenges for LA in higher education. Although the potential benefits of LA are increasingly more prominent for students, educators, and institutions of higher education, challenges have existed since the field’s inception. Recently, in reviews of literature by Avella et al. (2016) and Banihashem et al. (2018), the challenges inherit in the field of LA research were accentuated. First, in Avella et al.’s review of 112 articles, 18 were focused specifically on the challenges that exist in LA, ranging back to the inception of LA as a field of research (Fournier et al., 2011; Johnson et al., 2011). Similarly, in Banihashem et al.’s review of 247 articles, 24 focused on challenges in LA with the most recent being Wintrup’s (2017) review of ethics and student engagement, and Gasevic et al.'s (2016a) correlational study of ethics and privacy.

Challenges in learning analytics can be organized into a multitude of separate categories, which are highlighted in Tsai and Gasevic's (2017) review of LA literature. In total, the authors present six primary challenges within LA: shortages of leadership, shortages of equal engagement, shortages of pedagogy-based approaches, shortages of sufficient training, shortages of studies empirically validating LA's impact, and finally a shortage of LA specific policies. It is worth noting that the challenges in their review are outside of the realm of challenges that exist to technical encounters in data and systematic integration. This differentiation is important within the context of the current study that focuses more on the educational perspective. In essence, the technical challenges that exist within LA research are progressively being separated in reviews of LA literature, notably with Banihashem et al.'s (2018) systematic review, where in their review "learning analytics was considered from an educational perspective… Thus, it was not focused on technical aspects where data mining, algorithmic processing, data collection, and data analysis are important" (Banihashem et al., 2018, p. 7).

With these challenges in context, there are three primary categories from Tsai and Gasevic's (2017) work that inform this study. First, while the majority of research attempting to address equal engagement among stakeholders of higher education institutions has focused primarily on students, there is a considerable lack of studies centered upon other agents of institutions. Examples of these gaps include a lack of understanding as to what LA "is", where a UK study found that those within technical areas indicated the highest levels of awareness and understanding when compared to other heads of e-learning areas (Newland et al., 2015). This was reinforced by the results of Oster et al.'s (2016) study which found that technology professionals indicated higher levels of institutional readiness for LA when compared to other institutional stakeholders.

This evolves into the second challenge of their review concerning the shortage of sufficient LA training in place. The authors position this in context to the growing demands among higher education institutions for shortages of skilled individuals in LA (Norris & Baer, 2013). Additionally, programs who report successful adoption and implementation of academic analytics were found to have strong institutional training programs and skilled staff in analytics, which were key to successful outcomes (Goldstein & Katz, 2005). Faculty member's lack of training and understanding of collected data and LA as a concept is a prevailing phenomenon and the central population of this study (Amida et al., 2022; Bollenback & Glassman, 2018; Dringus, 2012; Ifenthaler, 2017), which again is an area of lacking research that feeds into this larger challenge of institutional readiness and adoption. To address these challenges, Wasson and Hanen's (2015) works on data literacy support the idea that relevant training should be supplied to all LA stakeholders by providing the skills to interpret and engage with the data being collected.

The third challenge that exists within LA research is a shortage of empirically validated studies demonstrating the impact of LA for a variety of stakeholders. While this emphasis on growing empirical backing for LA is a critical area, it goes beyond a scientific backing to the perceptions of institutions, where successful LA programs were able to "persuade senior staff who can allocate budgets to support learning analytics" (Newland et al., 2015; Tsai & Gasevic, 2017, p. 4). There are a few considerations to address in this overall challenge, the first being that LA adoption and implementation on a larger scale is in the early stages (Sclater, 2014) and has ultimately lacked any longitudinal assessment of success based on lag with data measurement (Arroway et al., 2016). Finally, as addressed in the benefits section of this review, although there are studies demonstrating the benefits of LA (Arnold & Pistilli, 2012; Lu et al., 2017), it is an area which needs considerably more empirical backing (Tsai & Gasevic, 2017; Viberg et al., 2018). While this summary of some critical areas in LA challenges gives a broader sense of the work that has been done and is yet to come, there is an additional area which needs further attention. One of the most frequently cited areas of LA research includes ethical, privacy, and legal considerations for a multitude of stakeholders in educational settings.

Ethics, Privacy, and Legality

Challenges and issues related to ethics, privacy, and the legality of data collection and analytics practices in LA are at the forefront of research. Early studies, such as Buchanan et al.'s (2007) development of measures for online privacy, note that the concept of privacy for online data was complex, and "despite the many attempts to create a synthesis of existing literature, a unified and simple account of privacy has yet to emerge" (Buchanan et al., 2007, p. 157). Parry's (2012) column on big data in higher education specifically mentions concerns with privacy and surveillance, particularly with the tracking of logins to Blackboard (i.e., an LMS) and a potential institutional connection to student ID card activity (i.e., the potential for social tracking). One of the first explorations of ethical considerations for LA came from Slade and Prinsloo's (2013) study defining ethical utilization efforts for LA which resulted in three categories of data interpretation, privacy and informed consent, de-identification of data, and the management/classification of stored data (Prinsloo & Slade, 2019). Additionally, Slade and Prinsloo (2013) proposed an ethical framework which focused on moral LA practices for students, with some considerations for transparency of data purpose and student agency serving as critical components.

In a review of ethical and privacy principles for LA by Pardo and Siemens (2014), the authors begin by addressing this growth in data collection and the potential for delicate information to be shared in the context of LA, where in the context of business analytics if data are collected from users a "transaction" takes place. The concern with this transaction comes to the forefront when contextualized with the trading of user's privacy for a service or potential benefit provided by those collecting the data. The growth of technology and the digitization of society included a series of directives and legislation in the US during the early tech growth era, but a "comprehensive definition of right to privacy in learning analytics research environments is equally elusive" (Pardo & Siemens, 2014, p. 442).

Other professional fields, such as medical research, have a longer history of addressing issues with ethical and privacy concerns related to data, where the authors make the argument that connections can be made with LA. The primary argument of working with population data in medical research is that it allows for advancement in the field, where the argument could be made for LA in how student data collection can help institutions advance research and benefit the future learning experiences of cohorts in higher education institutions. While this may appear to be an argument for full transparency and utilization of stakeholder data, including private, there are too many risks associated with more direct areas of funding and education policy. Contextually, data ethics and privacy policy within medical research is considerably more advanced than in LA, but there are specific elements within medical research data that spotlight components of LA.

Data ownership, a concept which has been in scientific literature since 1981 (Asswad & Gómez, 2021), is defined as "the possession of complete control over the data and its rights, including the right to grant rights over the data to others" (Asswad & Gómez, 2021, p. 1).

Recently, in a review of ethical issues in LA by Tzimas and Demetriadis (2021) data ownership has been identified as a complicated moral and legal issue in data management. Research on data ownership grew with the establishment of the internet and web 2.0 (Al-Khouri, 2012); Franklin & Harmelen, 2007). Pardo and Siemens' (2014) study was one of the first in the field of LA to address data ownership from a variety of stakeholder perspectives, specifically framing questions of how students can control the data that is used and shared, if the institutions, students, or third-party companies own the data, and ultimately if an individual accepts raw data ownership what happens with the analyzed data? This second point is important to contextualize as well, when third parties are often utilizing the raw stakeholder data for algorithmic and model development (Larusson & White, 2014; Pardo & Siemens, 2014).

Tzimas and Demetriadis' (2021) review also highlights that data ownership within LA has ultimately focused on student perspectives into the modern era of LA research (Hoel et al., 2017; Ifenthaler & Tracey, 2016), and that overlaps with other areas including algorithmic fairness and institutional obligation to act to support student success outcomes. Notably, research on faculty perspectives of data ownership with their own course data appears to be largely absent up to this point. Drachsler & Greller (2016) note that "at present, there is no clear regulation for data ownership of any party, i.e., neither the student, the university or a third-party provider. Data ownership is a very difficult legal concept" (Drachsler & Greller, 2016, p. 95). Additionally, defining data ownership in the field of LA research continues to be a complicated issue, and ultimately will continue to gather attention in both the field of LA and the data practices of higher education institutions. It is worth noting however that some policy has been developed in an attempt to address this concept from a broader perspective. Specifically, the EU Data Protection Directive provides protections where the data subject has the right to know what is being collected about them. More recently, with the passage of the General Data Protection Regulation (GDPR), Sclater (2018) notes that many of the processes in the LA data collection and analyzation processes must take into consideration that it is justified in one of the lawful bases for processing in the GDPR.

A final component of Pardo and Siemens (2014) research that informs the current study is the concept of fostering trust in LA initiatives and online platforms. The authors note that "Several studies have identified trust as one of the most important traits to improve user experience on the Internet" (Pardo & Siemens, 2014, p. 444), and contextually points out that other areas of technology use by students, including social networks (Toch et al., 2012) in the end carry over into the deployment of LA by institutions of higher education.

While there is a broad range of modern research centered upon ethical, privacy, and legal perspectives in LA, Drachsler & Grellers' (2016) development of DELICATE, a checklist to assist institutions utilization of LA, is one of the most cited efforts to address these prevailing challenges. The study notes that empirically, Scheffel et al.'s (2014) research identifies "data privacy" as a critical aspect for improving trust and increasing the quality of LA, and that up to that point there was limited research being developed or publicized concerning privacy and ethics in LA. Moreover,

> despite the enormous promise of learning analytics to innovate and change the educational system, there are hesitations regarding, among other things, the unfair and unjustified discrimination of data subjects; violation of personal privacy rights; unintended and direct pressure to perform according to artificial indicators; intra-transparency of learning analytics systems; loss of control due to advanced intelligent systems that force certain decisions; the impossibility to fully anonymize data;

safeguarding access to data; and, the reuse of data for non-intended purposes (Drachsler & Greller, p. 93).

Briefly, concerns related to discrimination and LA are an additional area of apprehension when working with data systems and ethics, where it has been argued that algorithms can enable digital discrimination in a relentless process of classification and categorization for the purpose of inclusion or exclusion (Norris & Lyon, 2003; Tsai et al., 2021). The authors also attempt to provide some definitions of ethics and privacy within the context of LA, where "ethics is a moral code of norms and conventions that exist in society externally to a person, whereas privacy is an intrinsic part of a person's identity and integrity" (Drachsler & Greller, 2016, p. 91). Additionally, "there exists a substantial overlap between ethics and privacy, which sometimes leads to confusion when discussing the effects of LA on either of them" (Drachsler & Greller, 2016, p. 90).

In summary, challenges surrounding LA as a field of research can be categorized in a variety of ways. Initially, a differentiation needs to be made between technological and educational practices, where one is focused on the algorithmic and analytical approaches and the other focuses more on the pedagogical and data informed decision making of higher education stakeholders. Some of the broader challenges that exist in LA include a lack of training and information transference among stakeholders, as well as a growing demand for empirical support of the benefits that LA can provide. Moreover, a critical series of challenges exist with respect to legal, ethical, and privacy concerns which appear to be drawing more attention in the literature as LA establishes itself as a field independent of other data initiatives of institutions. Among the common theme for challenges were data ownership, control, and trust as it pertains to LA data, which this study attempts to incorporate into a more specified understanding of what factors impact faculty perceptions and utilization of LA in their courses.

Faculty Motivation

Faculty Motivation Research

In reviewing the literature of faculty motivation, it is critical to begin by focusing on the importance of this line of research. Specifically, faculty have been identified as a top producer of innovative research (Javits et al., 2010) and contribute to several societal benefits including informed citizenship, scientific advances, and influence over economic activity in a variety of settings (Landry et al., 2003; Perkman et al., 2013; Weinberg et al., 2014). Javits et al.'s (2010) exploratory paper of scientific publishing notes that the academic sector of the scientific community in the United States is critical to the overall health of the research system. Where "university-based scientists generate the most publications and, arguably, conduct much of the most important and innovative research" (Javits et al., p. 4). Similarly, the role of faculty is also important in the cyclical process of recruiting and training the future generations of new researchers, emphasizing the importance of teaching.

Within the context of motivational theories, such as Deci and Ryan's (1985) Self-Determination Theory and Bandura's (1986) Social-Cognitive Theory, it is important to understand that research on faculty motivation has been identified as an area with limited research. Daumiller et al.'s (2020) encompassing special issue of higher education faculty members' motivation notes that in comparison to student and teacher motivation, limited research exists in comparison that specifically looks at the motivation of university faculty. This is a growing concern as there are multiple challenges that currently exist regarding the behavior of university faculty. Some examples include the plateau of publications in peer-reviewed journals even though research expenditures have increased over time in the United States (Litwin, 2014). Specifically, Litwin's (2014) study observed that per-capita, there was a significant decline in research productivity in United States colleges and universities between the years of 1996 to 2002. Moreover, Boroush (2020) notes that the United States has recently declined in research output to the point that it is now behind China and the European Union in citations for the top one percent of publications. Another major concern is related to pressures and challenges associated with teaching and the combatting of burn out and attrition reported by faculty in the United States (Padilla & Thompson, 2016), and internationally as well (Catano et al., 2010; Kinman et al., 2006). Most notably, Padilla and Thompson (2016) found that a variety of aspects contribute to the burnout of university faculty, where their study indicated that hours worked per week and pressure to perform well were significant factors in reported burnout.

Daumiller et al. (2020) specifies that while most research related to faculty performance has focused on factors such as institutional and socio-environmental, there is considerably less attention centered upon faculty motivation. The question then becomes, *why has the motivation of university faculty gone overlooked and understudied?* Reasons for this limited line of research include a limited workforce in a comparison with K-12 teachers, and misconceptions concerning the motivation of university faculty as being inherently high based on the investment of time and resources that goes into completing doctoral level study and a competitive academic job market upon degree completion (Woolston, 2015). Perhaps even more concerning, is that recent trends do not indicate any change with graduate student perceptions of what the academic job market and career expectations are like, with waning interest over time (Woolston, 2022).

Another critical reason for this limited line of research may also be associated with stressors and challenges related to the responsibilities of an academic career. Specifically, university faculty face a multitude of demotivators, with an example being the process of published research in peer-reviewed journals where fear of rejection can have a negative impact of engaging with this task in the future (Minter, 2009). Minter (2009) highlights how university faculty face a multitude of challenges within the academic model, including further advancement based on prolonged timelines (i.e., the transition from assistant to associate professor, tenure status) along with external factors that are fiscal in nature, "the reality is that a majority of U.S. universities are operating under tight budgets" (p. 67). There are a multitude of additional reasons for why faculty motivation may be understudied as well, these include the idea that faculty may be too overburdened and under pressure to participate in empirical lines of research (Catano et al., 2010; Winefield et al., 2008), and logistics such as sample size and sample diversity which could be generalizable to the greater population of university faculty.

Summarily, Daumiller et al. (2020) notes that "Collectively, the potential reasons for the lack of research on faculty motivation to date leads to a clear conclusion: this is a young and developing area of research experience normal growing pains that can be overcome" (Daumiller et al., p. 3). With that in mind, the question then becomes what theories are applicable for the study of faculty motivation, and what have previous studies focused on with respect to faculty motivation?

Motivational Theories and University Faculty

Although it has been recognized that studies surrounding faculty motivation is limited, it is a growing area of research which ultimately concentrates on psychological measures and explanations of faculty behavior in a variety of areas including teaching, research, and professional development. When questions arise about why theoretical frameworks are important to the study of faculty motivation a key component to identify is an emphasis on motivational types that exist versus a numeric amount or total motivation experienced. While it is important to measure faculty motivation quantitatively, specific theories are applied to better understand both quantity and quality as it relates to motivation experienced (Daumiller et al., 2020). This review of literature presents three current motivational theories established in faculty motivation research, one of which is the foundation and theoretical framework of this study, Deci and Ryan's (1985) Self-Determination Theory.

Bandura's Self-Efficacy Beliefs

One of the first theories established within the study of faculty motivation is Bandura's (1997) self-efficacy beliefs and model of motivation. Bandura's Self-Efficacy Beliefs construct is centered upon the subjective beliefs of an individual regarding whether they are able to engage with specific tasks successfully (Bandura, 2001). Self-efficacy beliefs for faculty motivation have been examined in research, where Major and Dolly (2003) conducted a qualitative study of new faculty hires at a research university and found that sources of self-efficacy in graduate programs were significant in academic tasks including research. Zhang et al.'s (2017) study on research and teaching also utilized self-efficacy among academics from higher education institutions in China to investigate and further establish the role of teacher/academic self-efficacy of emotions in teaching styles. While self-efficacy research has focused more within the context of research (Foreseter et al., 2004; O'Brien et al., 1998), there is a growing segment of self-efficacy research that is focused on the domain of teaching.

Daumiller et al.'s (2021) study on teacher motivation focused on faculty motivation and self-efficacy for student learning experiences through multilevel modeling. Key points in the studies literature point out that "teachers self-efficacy beliefs are presumed to be strongly tied to the decisions they make about choosing, investing effort in, and persisting with teaching activities" (Daumiller et al., p. 4; Woolfolk et al., 2009). The primary investigation of the study looked at how faculty motivation matters in student learning experiences in higher education, particularly with student perceptions of teaching quality and emotional experiences. The results found that teacher's general self-efficacy beliefs were a resource for positively perceived teaching, and overall that faculty motivation was associated with "students' perceived teaching quality and emotional experiences, we found that this association was not trivial, and that the specificity of motivations needs to be accounted for" (Daumiller et al., p. 11). As suggested previously, motivation types along with quantity are important considerations in order to understand faculty motivation for academic practices. Where in closing, Daumiller et al. state that "the main take-away message is that the specificity of motivation and, thus, the operationalization of motivation within research designs and questionaries, strongly matters for research on the effects of teacher (faculty) motivations" (Daumiller et al., p. 12).

Faculty Emotions (Pekrun's Control-Value Theory)

Another important theoretical component for faculty motivation is contained in their emotional experiences. Contextually, emotions are central to component for the experiences of individuals, and affect physiological, behavioral, and motivational experiences (Daumiller et al., 2020; Pekrun, 2006; Stupnisky et al., 2016). Recent studies have identified faculty emotions as broad ranging to include both positive and negative emotions, along with enjoyment and frustration in the context of teaching and research (Kordts-Freudinger et al., 2017; Stupnisky et al., 2016). Pekrun's (2006) Control-Value Theory of achievement emotions acts as a framework for "analyzing the antecedents and effects of emotions experienced in achievement and academic settings" (Pekrun, p. 315). In a study by Stupnisky et al. (2019) that analyzed the role of emotions in predicting faculty teaching and research performance, they described control-value theory as positing that "individual's assessments of perceived control and value within given achievement situations are central to determining what emotions they experience, which in turn affect performance" (Stupnisky et al., p. 1714). Utilizing structural equation modeling, the study found that emotions significantly related to faculty member's perceived success both in research and teaching when factoring in social-environment factors. Notably, the models indicated that anxiety, followed by enjoyment, were the strongest predictors to faculty member's success in both teaching and research.

The final theoretical perspective, and ultimately the theoretical framework of this study, is Deci and Ryan's (1985) Self-Determination Theory, which emphasizes the prevailing theme of both quality and quantity of motivation experienced.

Self-Determination Theory

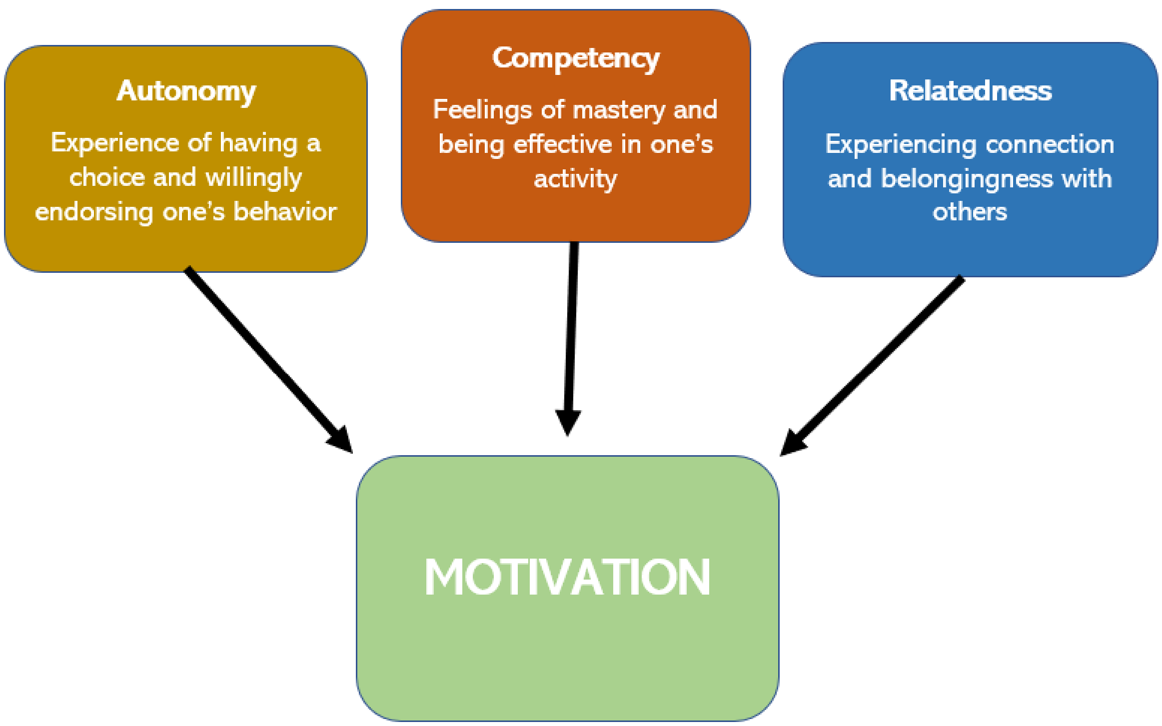
Deci & Ryan's (1985;1985a) Self-Determination Theory (SDT) is an empirically established theory of human behavior which focuses on psychological measures of human motivation. Specifically, SDT "examines how biological, social, and cultural conditions either enhance or undermine the inherent human capacities for psychological growth, engagement, and wellness, both in general and specific domains and endeavors" (Ryan & Deci, 2017, p. 3). In a recent review of SDT research from Ryan and Deci (2020), the authors emphasize that SDT assumes individuals are "inherently prone toward psychological growth and integration, and thus toward learning, mastery and connection with others" (Ryan & Deci, p. 1). The critical caveat with this assumption however is that our human activities or tendencies are not automatic, and they need supportive conditions to be healthy or robust. Motivational theories such as SDT are critical in understanding human behavior through psychological models as it informs causal models. Specifically, SDT is important in describing and predicting motivated behaviors where if we wanted to predict faculty utilization of LA in their courses, we would need to understand what factors or regulations support or thwart this specific behavior (Ryan, 2012). Moreover, it is a critical concept within the SDT framework that motivation is focused more on the types of motivation as predictors of behavior/outcomes rather than the strength or amount of motivation being displayed (Deci & Ryan, 2008a; Howard et al., 2016; Stupnisky et al., 2018).

SDT has been established as an empirically sound theoretical approach to understanding the motivation and behavior of individuals in a variety of settings; including psychology (Gagné & Deci, 2014), medical education (Kusurkar et al., 2011; Ten Cate, 2011), banking (Hussain et al., 2015), health and exercise (Hagger & Chatzisarantis, 2008; Ng et al., 2012), K-12 education (Reeve & Halusic, 2009), student engagement (Reeve, 2012), and higher education (Jeno et al., 2018). More recently, Ryan and Deci (2020) have emphasized the importance of SDT research in learning and technology. Specifically, in a review of studies concerning SDT in education, the authors emphasize that "Future SDT research will no doubt be looking more closely at how educational media, e-learning, remote classrooms, and other opportunities afforded by technology can be successfully created to motivate engagement and learning" (Ryan & Deci, 2020, p. 8). The founders of SDT also provide an influential statement that supports the critical nature of the current study, "students' and teachers' motivation to use technology as a tool for learning will become an even more active area of research" (Ryan & Deci, 2020, p. 8).

The initial concept to understand within SDT is the role of *autonomy,* where being autonomous "means to behave with a sense of volition, willingness, and congruence; it means to fully endorse and concur with the behavior one is engaged in" (Deci & Ryan, 2012, p. 85). SDT also posits that three basic psychological needs are required for optimal functioning, growth, and integration, and are categorized as *autonomy*, *competency*, and *relatedness* (see Figure 1). Within the context of LA, these three basic psychological needs would be reflected if a faculty member feels a sense of freedom to utilize LA in their courses (autonomy), skilled in their ability to analyze and interpret course data (competency), and a sense of closeness or relatability with other faculty who utilize LA in their courses, or the students who may benefit from LA course implementation (relatedness).

Figure 1

Conceptualization of Self-Determination Theory Basic Psychological Needs



Note. Based on the work of Ryan & Deci (2000)

Self-determined motivation involves internal motivation through *intrinsic*, *internal*, and *identified regulation*. Intrinsic motivation for LA involves a faculty member's perceptions and utilization of LA as being reflective of inherent interest or enjoyment, along with identified regulation where actions are performed for their perceived importance or value. However, on the non-self-determined side exists *external regulation*, or *extrinsic regulation*, where motivation is influenced by outside factors. *Introjected* motivation is a form of internal regulation/motivation where an individual performs an action to avoid guilt or anxiety, whereas external regulation would entail faculty utilization of LA based on the avoidance of punishment (e.g., contractual obligations to incorporate LA practices in courses) or the potential for external rewards (e.g., salary increases for implementation of LA practices in courses). It is worth noting that recent research has highlighted both positive and negative interpretations of introjected regulation, where in positively introjected regulation a faculty member would utilize LA in their courses to boost their self-esteem, or negatively regulated behavior for avoidance of guilt for not integrating LA practices (Sheldon et al., 2017; Stupnisky et al., 2019). On the opposite end of the spectrum from autonomous motivation is *amotivation*, where a faculty member would display a degree of uncertainty, lack of value, or purpose in why they should utilize LA practices in their courses (see Figure 2). In general, amotivation is an absence or lack of volitional drive to engage in activities or behaviors (Deci & Ryan, 1985), and ultimately results from motivations which lack self-determination (Banerjee & Halder, 2021; Markland & Tobin, 2004). Specifically, as it relates to academic tasks, "placing little or no value on academic tasks (i.e., amotivation-low task value) means there exists no intrinsic or extrinsic (i.e., autonomous or controlled) incentive to participate which increases amotivation and task avoidance" (Banerjee & Halder, 2021, p. 2).

For the purposes of this study, the spectrum of regulation/motivation types are classified into *autonomous* and *controlled* motivation for LA, where autonomous motivation is the combination of intrinsic and identified regulation types, and controlled motivation is the combination of introjected, and external regulation. This employment of measures has been previously utilized based on the high correlation among regulation types into autonomous and controlled forms of motivation (Daumiller et al., 2020; Guay et al., 2015; Stupnisky et al., 2018;2019; Van den Broeck et al., 2011). There are some considerations to take however in the formation of a controlled motivation construct, with mixed results in how external regulation correlates with introjected regulation types (i.e., positive, and negative).

Figure 2

The Self-Determination Theory Continuum of Motivation in Learning Analytics

Controlled Motivation			Autonomous Motivation	
Amotivation	Extrinsic Motivation			Intrinsic Motivation
Amotivation	External Regulation	Introjected Regulation (+/-)	Identified Regulation	Intrinsic Regulation
Based on a lack of perceived competence, missing value, and a potentially high perceived cost	Based on external rewards and punishments, compliance with authority, and reactions to the environment	Based on approval from both self and others, pride, shame, and ego involvement	Based on personal importance, conscious value, self-endorsement, and goals	Based on interest, enjoyment, or inherent satisfaction with a task
"I don't know why I should use learning analytics in my courses"	"My contract requires that I use learning analytics in my courses"	"I would feel guilty not using learning analytics in my courses"	"Using learning analytics is important to me"	"It is enjoyable to use learning analytics for my courses"

Note. Based on the works of Ryan and Deci (2000) and McEown and Oga-Baldwin (2019)

Self-Determination Theory and Faculty Motivation

In recent years, the utilization of SDT to better understand faculty motivation in topics such as teaching, and research, has developed as an increasingly important theoretical approach. Stupnisky et al.'s (2018) study of faculty motivation for teaching and best practices was one of the first to utilize measures of basic psychological needs and motivation types to better understand faculty teaching in best practices. The study initially highlights the importance of studying university faculty, especially their teaching, where the "quality of faculty teaching, in turn, affects college student engagement and deep approaches to learning" (BrckaLorenz et al., 2012; Stupnisky et al., 2018, p. 15; Umbach & Wawrzynski, 2005).

Stupnisky et al. (2018) note that empirical research focused on the role of motivation in teaching is limited, with early inclinations as to its appropriateness linked to Deci et al. (1997), where intrinsic motivation could explain teaching in relation to basic psychological needs. It is worth unpacking that although literature surrounding faculty motivation through SDT is limited, there are studies which have focused on K-12 teachers in measuring autonomous motivation for training engagement (Aelterman et al., 2016; Gorozidis & Papaioannou, 2014), and Flassen et al.'s (2012) study that found teacher satisfaction and met criterion of autonomy, competency, and relatedness predicted higher levels of engagement with more positive than negative emotions. The literature supporting the SDT framework for faculty is considerably more limited, where Cook et al., (2009) in a compilation of data from four studies found that intrinsic motivation was significant in faculty teaching of distance courses, which was also a more endorsed reason than externally regulated components including financial rewards. Additionally, Stupnisky et al. (2017) found that intrinsic motivation was significantly predicted by faculty relatedness which led to perceived teaching success.

Utilizing data from the 2016 Faculty Survey of Student Engagement (FSSE), Stupnisky et al. (2018) employed structural equation modeling to discover that satisfaction of the three basic psychological needs during teaching (i.e., autonomy, competency, and relatedness) predicted greater autonomous motivation. Additionally, the satisfaction of basic psychological needs did not relate to controlled motivation for teaching. One of the critical results of this study was also that autonomous motivation "was a positive significant predictor of teaching best practices, whereas the two types of controlled motivation were not significant predictors" (Stupnisky et al., 2018, p. 23).

An additional study from Stupnisky et al. (2019a) employed SDT to better understand faculty research success. Emphasizing again the limited research that has been done to apply SDT to the role of faculty, previous studies have utilized motivation to better understand research productivity and success. Examples being Bland et al.'s (2005) study of medical school faculty which found that the highest predictor of high research productivity was motivation. Similarly, Hardré et al. (2011) found that intrinsic motivation for research had a significant positive effect on the perceived value of faculty members in conducting research (Stupnisky et al., 2019). In a large sample of faculty who completed the FSSE, structural equation modeling again found that elements of basic psychological needs predicted autonomous motivation for research. Specifically, autonomy and competence were positive predictors of autonomous motivation among faculty members, while relatedness was not significant. Finally, autonomous motivation for research "was the strongest significant predictor of perceived research success and number of publications" (Stupnisky et al., 2019, p. 32).

Self-Determination Theory in Learning Analytics

The utilization of SDT as a theoretical framework for this study was important because it addresses challenges inherent in LA research. First, in order to better understand faculty perceptions and utilization of LA, further empirical support is needed to identify theories which can specifically address educator's perspectives and actions related to the utilization of LA practices and tools in their courses. As mentioned earlier in the review, there are a variety of theories and models that exist surrounding LA and faculty perceptions of technology, including Arnold et al.'s (2014) Learning Analytics Readiness Instrument (LARI) for institutions, and the Davis (1989) Technology Acceptance Model (Silva, 2015; TAM). The challenge remains, however, in establishing theories that directly address educator buy-in and motivation for LA utilization. Previous studies have looked at the motivation of faculty to adopt technology, such as Gautreau's (2011) study on faculty motivation for and use of learning management platforms, where these LMS platforms contain a series of tools for LA practices with course data.

Additional studies have also looked at the adoption of classroom technology through perceived usefulness and intention by faculty (Ajjan & Harthshorne, 2008). More recently, SDT has gained considerable attention in theoretical application to LA research, where SDT "can inform the creation of conditions to motivate learners to engage with uninteresting tasks" (Matcha et al., 2019, p.14). SDT has also been utilized in a variety of studies to understand student engagement with LA practices and technology integration, especially in online, flipped classroom, or blended learning course delivery methods (Ameloot & Schellens, 2018; Sergis et al., 2018).

Throughout a review of literature on faculty perceptions and utilization of LA, components of SDT basic psychological needs and motivation types appear superficially to the theoretical framework. Examples include faculty member's sense of autonomy in LA (Brown, 2020; Hora et al., 2017; Johnson, 2017; Svinicki et al., 2016), relatedness (i.e., cooperation; Svinicki et al., 2016), and motivation (Amida et al., 2022; Drachsler & Greller, 2016; Johnson, 2017; Scheffel et al., 2014). This occurrence of common terminology in understanding faculty perceptions and utilization of LA provides further evidence to apply an empirical approach to this area of research through the deployment an SDT framework.

Faculty Motivation for Learning Analytics

While research concentrating on faculty motivation is a limited but growing area, the motivation of faculty to utilize LA is very inadequate. This lack of research is concerning for a multitude of reasons. First, previous studies suggest that the multiple benefits, including improved teaching effectiveness (Sclater et al., 2016) would be beneficial for university faculty. Overall, studies looking at motivation in the field of LA has gained some traction but have been primarily focused on student or K-12 teacher perspectives and experiences. Scheffel et al.'s (2014) framework of quality indicators for LA for LA tool evaluation is one of the first studies to include both student and teacher motivation considerations, and ultimately proposes five criteria as quality indicators for LA, one of which in objectives includes motivation.

Research concentrated on motivation for LA has typically been centered on students, where student perceptions of LA platforms influenced their motivation (Lonn et al., 2015), dashboard use by advisors related to changes in student motivation (Aguilar et al., 2021), and LA based feedback showing effectiveness in impacting student motivation (Karaoglan et al., 2021). Research has also been done to ground SDT and existing empirical evidence to support goal-setting and collaborative learning in LA designs (Marzouk et al., 2016), of which the study notes the application of motivational theory is in the early stages in the context of LA. Johnson (2017) cites self-determination and autonomy in speaking to ethics and justice concerns in LA, but ultimately does not link them to SDT; similarly, in Drachsler and Greller' (2016) study on privacy and trust in LA. In the preliminary search, only a few studies thus far have focused on motivation for LA through the lens of SDT, with only one concentrated on faculty. Schumacher and Ifenthaler (2018) note that their study on student motivational dispositions is "a first attempt at linking empirical evidence, motivational theory, and learning analytics" (Schumacher & Ifenthaler, 2018, p. 599). The study highlights how LA can provide motivational interventions, based on a variety of LA benefits including real-time feedback and the evaluation of learning outcomes. However, their study does not mention the role of faculty as it links between motivational theories and learning analytics utilization.

Amida et al. (2022) utilized a mixed methods study to understand faculty member's perceptions of LA with respect to how it could improve teaching through the lens of SDT and Eccles' (1983) Expectancy-Value Theory. This is one of the first studies to quantitatively measure faculty members motivation, specifically through measures of SDT, for LA tool utilization. The study highlights that even though there are a potential series of benefits presented to stakeholders of higher education, faculty remain skeptical of LA's value (Corrin et al., 2013). The study utilized Sclater's (2017) four major areas of LA application in survey development, which includes early alert, course design, course recommendations, and adaptive learning.

Early alerts and kudos are procedures to identify students who may be at risk of failure in a course, whereas kudos are a form of positive feedback to students who are high performers in a course (Sclater, 2017). Traditionally, early alert systems are linked with the tracking of student activity in courses, where either automatic process (i.e., algorithmic functions which collect course data and alert faculty members) or manual processes (i.e., manually checking student activity) inform intervention (Villano et al., 2018). The Purdue Course Signals program is one of the most frequently cited examples of a system which utilizes early alert processes (Arnold & Pistilli, 2012).

Amida et al. (2022) utilized SDT to measure regulation types (e.g., intrinsic motivation, external motivation, introjected motivation, and amotivation) in combination with Expectancy Value measures (e.g., utility value, cost value, and attainment value) to predict faculty members LA tools utilization and self-perceived teaching effectiveness. With the prevailing LA literature suggesting that it should be used to inform teaching practices and improve courses (Gašević et al., 2016; Siemens & Long, 2011; Stewart, 2017), few studies had examined how LA utilization could inform a quantitatively measured faculty members' perceptions of their teaching effectiveness.

Results were two-fold in quantitative and qualitative phases. First, path analysis revealed that faculty perceptions of LA cost, utility, and attainment were all significant predictors of intrinsic motivation for LA, as well as negative predictors of amotivation, where faculty may be uncertain of the value or utility of LA. Additionally, the use of single-click LA tools (e.g., monitoring student performance) and multi-click LA tools (e.g., downloading course data to examine student performance) did not predict or correlate with faculty members perceived teaching effectiveness.

Qualitative results from focus groups revealed seven themes which were coded from 144 significant statements on questions related to LA perceptions, motivation, demotivating factors, and how faculty were currently using LA in their courses, if at all. Among the findings were that faculty primarily used LA in their courses to track and monitor student activity, as well as alert them of declines in performance. This was also supported by the quantitative results where 86.3% of faculty monitored students' performance through a grade center in Blackboard (i.e., LMS), and 72.9% alerted students about poor academic performance based on course data. Challenges that were revealed in focus groups ultimately connected with the prevailing challenges cited in this review of literature surrounding LA, primarily in faculty struggling to understand the balance of cost and time with the potential benefits of LA, a lack of data competency in accessing and interpreting what was being collected in the LMS, and concerns over the unstructured nature of the data and potential impact or meaningfulness of what is being collected.

A secondary goal of this study is to further establish SDT as an appropriate theoretical lens to understand faculty motivation for LA, and understand what factors ultimately promote or inhibit faculty application of LA in their courses. This approach further supports the utilization of empirically established motivation or emotion-based theories to better understand the behaviors and attitudes of faculty to adopt LA practices in their courses.

Faculty Perceptions and Utilization of Learning Analytics

Research focusing on the perceptions and utilization of LA for university faculty is limited and was an important element for the foundation of this study. One of this studies' primary goals focused on why university faculty are willing to engage with learning analytics, and moreover how motivation plays a role in this adoption of LA practices. Previous studies have focused on Adams et al.'s (1992) Technology Acceptance Models (TAM; Herodotou et al., 2019), while also utilizing the academic resistance model. Where TAM has been posited as an appropriate theoretical framework to understand the perceptions of academics and their utilization of LA.

Stated previously, studies on faculty perceptions and utilization of LA are a limited area for empirical research, and ultimately is more associated with previous studies in technology adoption than direct LA practices in their teaching or learning environments. Examples include Mitra et al.'s (1999a;1999b) studies which found that faculty who identified technology use to have positive effects on their teaching were more likely to utilize it, and Spotts and Bowman's (1995) study which posited that once faculty become more knowledgeable about the technology they are utilizing, the more frequently they implement it.

Early Research on Faculty Technology Perceptions

Ajjan and Harthshorne's (2008) study is one of the first to focus on faculty perceptions and decisions to adopt technologies in Web 2.0, which at the time was focused primarily on wikis, blogs, and social media. This study is a continuation of results posited by Tornatzky and Klein (1982), where innovation in general is more likely to be adopted by individuals when job responsibilities and the value systems of said individuals are considered. Ajjan and Harthshorne (2008) employed a series of hypotheses that measured concepts such as faculty attitude and perceived ease of use for Web 2.0 technologies. Attitude dealt with faculty member desirability to utilize Web 2.0 technologies for in-class learning, and perceived usefulness dealt with the degree to which the faculty member viewed Web 2.0 technology as being useful in enhancing their classroom effectiveness. An additional measure focused on perceived behavioral control, in other words, the faculty member's perception of perceived behavioral control regarding resources and self-confidence (i.e., intention to use Web 2.0; Ajjan & Harthshorne, p.74). Finally, self-efficacy, a motivational theory cited in the current study's review of literature, was also utilized to understand faculty judgment of their own capabilities to use Web 2.0 to support their in-class learning environment.

Results of the study through path analysis and regression models found that faculty attitudes and perceived behavioral intention were strong positive influences on utilization of Web 2.0 technology. Notably, "only self-efficacy was found to influence the perception of behavioral control" (Ajjan & Harthshorne, p. 79). These results are significant in not only highlighting multiple factors that influence faculty perceptions and adoption of technology (in this instance Web 2.0), but also introduces a measure of motivation in self-efficacy to understand the potential relationship it has in faculty utilization of technology to enhance their learning environments.

Tabata and Johnsrud (2008) also conducted one of the first studies to understand faculty attitudes and utilization towards technology in distance education. Through survey analysis of full and part-time faculty members, the study centered on dimensions of attitude toward technology, adoption of innovations, and other instruments focused on distance learning. Among the various results, the study found that "using technology in ways that are relevant and meaningful (i.e., enabling faculty to conduct their work) plays an important role in encouraging participation in distance education" (Tabata & Johnsrud, 2008, p. 635). Overall, the results suggested that faculty participation in distance education played a role in their skills and attitudes toward technology, calling for additional understanding of faculty attitudes and technology utilization practices. Notice, these studies were empirical attempts to understand faculty perceptions and adoption of technology practices in teaching and were conducted before the establishment and streamlined definition of what LA was as its own field of study. Up until this point, the research had been focused on e-learning analytics, data mining, and academic analytics (Campbell et al., 2007; Romero & Ventura, 2007; Vivekananthamoorthy et la., 2009), which ultimately go on to comprise major components of LA as a new field of study. It is worth mentioning, that the perceptions of faculty towards areas of research that ultimately formulate LA included early observations of "skepticism", specifically towards academic analytics (Campbell et al., 2007; Parry, 2012).

The Development of Learning Analytics and Faculty Perceptions

One of the first studies to focus on faculty perspectives in LA as a newly established field of research was Dietz-Uhler and Hurn's (2013) study on using LA to predict and improve student success with an emphasis on the faculty perspective. Notably highlighting the idea that LA could improve student success by predicting performance and supporting retention efforts by allowing faculty and institutions to make data-driven decisions. The basis for this study was also grounded in the idea that faculty at this point were ultimately collecting or accessing data from LMS' at their current higher education institutions. One of the key preliminary suggestions of this study was the proposition that up until that point, faculty were ultimately reliant upon institutional hunches or self-observation to "know when students are struggling, or to know when to suggest relevant learning resources, or to know how to encourage students to reflect on their learning" (Dietz-Uhler & Hurn, p. 20). This was also one of the first studies to highlight the types of data that faculty have access to through their institution's LMS platform, which included both student data in number of material accesses, number of discussion posts read, and date/time of resource access. This also included data generated by instructors, such as grades and interactions with students via e-mail or discussion forum.

While the study does include potential benefits of faculty using LA in their courses, this has been covered in a previous section of the current study and allows for further elaboration on some of the earliest proposed concerns or issues for faculty in LA implementation. Dietz-Uhler and Hurn (2013) go on to emphasize four concerns regarding LA for faculty, which included the concept of "Big Brother", where it would be perceived as threatening that faculty could know someone witnesses and track all that they do. Additional concerns involved a holistic perspective where the comprehensive nature of collected data would miss additional issues such as those of student interpersonal experiences, greater faculty involvement/investment in LA to notice worthwhile impact, and finally a sense of faculty obligation to act on the data in order to increase student probability of success in their courses. These concerns were however a continuation of Dringus' (2012) work which was one of the first to caution about the benefits of LA, arguing that it could be harmful if there is a lack of meaningful data, transparency, reliable algorithms, and effective data utilization by faculty and institutions. Dietz-Uhler and Hurn (2013) conclude their paper by noting the growing momentum for this new field of LA and suggest that even though these implementations of data to improve teaching are small-scale, they could have a significant impact on student success.

Continuing with this line of research to better understand why faculty utilize LA practices in their courses, Svinicki et al. (2016) explored the factors that influence faculty adoption or rejection of using course data to improve instruction. This study was one of the first to utilize measures of motivational theories in understanding faculty adoption of LA practices (e.g., course data analysis). One of the key points presented early in the study was the differentiation between "action research" and LA, where action research is argued to be more aligned with teacher questions, rather than the analysis of data which has already been collected (Dyckhoff et al., 2013). Svinicki et al.'s (2016) study is especially important because it is one of the first to focus on faculty behavior to gather and use student data collected in LMS platforms. Specifically, the authors utilize five prominent theories which included psychometrics in Bandura's (1986) self-efficacy component of Social Cognitive Theory, Wigfield and Eccles (2000) Expectancy Value Theory of motivation, Deci and Ryan' (2000) Self-Determination Theory of motivation, Madden et al.'s (1992) Theory of Planned Behavior, and finally Rogers (2003) Adoption or Diffusion of Innovations theories.

The authors utilized these theories by measuring several factors housed within each. Examples include self-efficacy which focused on a teacher's belief in their own abilities to collect and interpret student data for course improvements, and faculty members autonomy or control which they must engage in the task of student data collection and utilization. In total, the authors propose four research questions which centered upon self-efficacy for collecting and utilizing student data, faculty beliefs about the value of student data, faculty perceptions of feasibility with collection and analysis of student data, measurement of outcomes, and relationships between factors and outcome variables. In a sample of 41 faculty, participants completed a survey and were given the opportunity for an interview to gather in-depth information to inform survey responses.

Results from the study were two-fold: First, roughly 50% of the faculty were utilizing student data for course improvement, and faculty reported self-efficacy was an acceptable predictor of faculty utilization of the data. The faculty also reported “having the authority to modify instruction based on data, the support of the administration to do so, and the flexibility to modify their course” (Svinicki et al., 2016, p. 6). Notable however is that faculty did not particularly value student course data for improving student evaluations, and faculty confidence did not indicate that there were enough resources to gather and utilize the student data collected in their courses. Additional quantitative results found that there was an overall positive impression of student data being used for course improvement and an overall faculty belief that it was feasible to collect student data for improvement.

Qualitative results suggested that the value of student data was “the most frequently mentioned comment made in the faculty interviews” (Svinicki et al., 201, p. 6), and an overall lack of resources to gather data for course improvement. It is worth mentioning the overall limitations of this study, notably with the small sample size for quantitative analysis, reliance on self-reported data, and a termination of intervention post measures that would have allowed the authors to provide additional resources to faculty for post-intervention analysis. In closing, the authors mention that research in the LA community should focus on development of instruments which could be generalized to better understand faculty utilization of student course data, where “analyses and presentations of data often rely on very complex models” (Svinicki et al., 2016, p. 9). While SDT was incorporated into factor development for this study, it did not ultimately measure the three basic psychological needs or motivation types on a continuum in the study measures, focusing more on autonomy as a sense of control over collection and analysis of student data.

Faculty Action Research and Data Driven Decision Making

In line with the previously mentioned concept of action-research (Dyckhoff et al., 2013), another term associated with faculty perceptions and utilization of LA is data driven decision-making (DDDM). DDDM is defined as “the systematic collection, analysis, and application of many forms of data from a myriad of sources in order to enhance student performance while addressing student learning needs” (Schifter et al., 2014, p. 420). In a study of DDDM, Hora et al. (2017) focused in part on what cultural data practices faculty were engaged in, and more so the role of DDDM in higher education going forward. The basis, in part, for this study was that “little is known about how faculty think about and use teaching-related data as part of their regular work and the roles that postsecondary institutions play in supporting the effective use of educational data” (Hora et al., 2017, p. 393). Moreover, the authors also point out that limited empirical research exists which attempts to understand how faculty perceive and use data as part of their instructional practices.

Hora et al.’s (2017) study utilized interview and observation data from 59 faculty to examine institutional support for the effective utilization of teaching-related data to improve educational practice. Results indicated that among characteristics which shape faculty utilization and implementation of educational data were themes associated with faculty members data expertise, social collaboration to work with data, and a variety of goals to analyze the data for documentation of student understanding and course/curriculum improvement. Faculty reported constraints and affordances which impacted data use reveal a series of important findings as well. First, faculty indicated that lack of time and heavy workloads were influential in engaging with student data, especially for those who had a primary obligation of teaching. Second, an additional constraint for faculty was centered on lacking expertise to work with educational data, specifically with limited ability to identify patterns and construe implications, as well as data management. Third, faculty also indicated that poor data quality was another constraint, this was however focused primarily on end-of-semester student evaluations and associated with response rates and time of delivery challenges.

In closing, the study notes that many faculty were engaged in some type of DDDM at their given institutions, but it was heavily reliant upon terminology and how DDDM was defined. Examples being that some faculty focused on statistical analysis of numeric data, and others who met to discuss course results with other instructors. Another key finding highlights faculty reliance on expertise with data analysis and DDDM, where "faculty appear to rely on their institution and/or expertise" (Hora et al., 2017, p. 417). While this is concerning, the authors do note that many faculty were engaged in data-related practices that focused on themselves or their students, and there is an opportunity to increase this by focusing on factors such as incentives for faculty to engage with DDDM in their courses. The authors elaborate on this by pointing out a lack of time for faculty to reflect on and act with their data, and ultimately a higher degree of autonomy needed to collect or analyze data based on a lack of incentive structure, "there simply was no compelling reason to commit scarce time to the design and implementation of a continuous improvement system" (Hora et al., p. 419). The authors reiterate concerns as well about data quality, specifically with student evaluations, where faculty indicated the data measures were poorly designed, lacked detail, and were untimely for actionable changes. Among the authors' final suggestions for institutions and policy makers, were that DDDM training should be implemented in graduate study to promote instruction through scientific inquiry, and an improvement to student evaluations.

Additional research on academics' perspectives of LA was investigated by Howell et al. (2017) through focus groups and thematic analysis that emphasized educator knowledge, attitudes, and concerns about the utilization of LA. An early point of emphasis in the author's work is that limited research had examined the perspectives of academics within LA. Notably, while academics do view potential benefits in utilizing LA for teaching practices, there is also a degree of skepticism towards the utility of LA (Corrin et al., 2013; Miles, 2015). The authors highlight the series of benefits and challenges that arise in LA literature concerning academics, the majority of which is covered previously in the studies of West et al. (2016), Corrin et al. (2013), and the early works of Drachsler and Greller (2012).

Thematic analysis revealed five key themes in the facilitation of learning, safeguards, concerns about students, concerns about academics, and moving forward with collaboration among stakeholders. Within the theme "facilitating learning" most academics indicated some awareness to what LA is and its utilization to develop predictive models to improve student retention, as well as viewing LA as capable to provide information to inform early intervention for students who may be at-risk. The theme "where are the safeguards?" highlighted academics' concerns surrounding the ethical use of LA, its appropriate utilization, data quality, and the potential redundancy of LA systems. Specifically, "The greatest concern expressed by academics was the potential for learning analytics to be used inappropriately, for purposes other than student learning" (Howell et al., 2018, p. 8). Notice, a key result from this theme connects with the purposes of our current study by highlighting academics' concerns that LA could be utilized for corporate purposes, "we start off with something that's aimed at better teaching… it gets hijacked into meeting requirements from government, or requirements from the senior executive team, or whoever. It ends up as an admin task that we have to do" (Howell et al., 2018, p. 8). Additionally, significant emphasis was placed on the quality of data being collected, more so if that data was accurately reflecting student activity, an example of which included lecture recordings, "if you allow students to download [rather than stream] then you don't know whether they viewed it or not anyway and so those data are meaningless" (Howell et al., 2018, p. 10).

In the theme "What about us!", academics expressed concerns related to workloads and who would be responsible for implementing and acting upon LA practices. This was associated with automation processes of LA, where appointments with students or intervention could become overwhelming for faculty who already work with limited time, and also included concerns about lacking support if LA became a greater part of the workload, "I would hate to see this become an expectation of people's workloads, without having the support that they need to use it effectively" (Howell et al., 2018, p. 14). Finally, the last theme reiterated a sense of multiple stakeholders working together, more so that academic and student perspectives would be included in the implementation of LA initiatives by higher education institutions, "sometimes I think this project is driven by the IT people… Not the people who actually work on the ground" (Howell et al., 2018, p. 14). Overall, the results of the study highlighted the need to include and engage academics in the LA process, as they are one of the key user groups.

The Growth of Research on Faculty Perceptions and Utilization of LA

In another qualitative study, Khan et al. (2017) focused on the perspectives of faculty, learners, and other staff at a university through a case study approach. In a post-positivist research approach, the author posed a series of research questions that asked about perceptions of LA among major stakeholders, who the wider stakeholders of LA were at the institution, and what challenges existed in LA as indicated by the stakeholders. The results found that academic staff were aware of LA, defining it as measuring some data about learners, and ultimately revealed that they would be interested in a variety of data which could be used to enhance teaching. Additionally, academics indicated a challenge in utilizing LA data to observe patterns or predict situations where they could intervene.

Bollenback and Glassman's (2018) study was one of the first to focus on the differentiation of faculty rank and LA adoption in courses, specifically by analyzing perceptions of LA amongst adjunct faculty members. Citing many of the studies included in this review, the authors note that there are pros and cons to LA in teaching practices, but there were however a series of challenges highlighted in Dringus' (2012) study including lack of faculty and staff training to interpret data, and that the data quality may not be a true indicator of student performance. Interestingly, the authors note that adjunct faculty were the population of focus based on their increased likelihood to have contact with LA at the course level. Through a mixed-methodologies approach, 113 adjunct faculty responded to a series of questions related to their desire to use LA in their courses and programs.

The results found that the majority of adjunct faculty participants agreed that LA "should be used by course developers to monitor how faculty achieve the learning outcomes and adjust as necessary" (Bollenback & Glassman, 2018, p. 75), with additional majority agreement on receiving feedback on student learning outcomes. However, the sentiment changed when faculty indicated that LA was being utilized to monitor classroom performance, with 62% agreeing that faculty performance reviews should contain data on student performance against learning outcomes. Moreover, faculty were "less interested in using analytics data to compare their performance with other faculty teaching the same course" (Bollenback & Glassman, 2018, pp. 75-76). As an aside, it is worth pointing out that this is one of the first LA based studies to include faculty performance and evaluation items, especially when making a comparison between student performance and comparisons among colleagues. Focusing on the results, faculty overall (74%) agreed that LA had some value, but there was also a high percentage of uncertainty. Moreover, the majority of faculty (73%) indicated that they would use LA in their courses if provided with proper training.

In the qualitative phase, a few themes emerged: Primarily that LA does provide good data for faculty member's respective universities, and LA could improve faculty performance and provide proof of learning objective attainment to accreditors. Concerns were also identified in the themes as well, and included concerns of how the data was being used and if it would identify faculty as "bad" if students were not meeting learning objectives. These results are critical in not only understanding faculty perceptions of LA, but more so initiating the conversation on the role that LA could play in performance evaluation and assessment as it relates to student performance objectives and faculty teaching performance/quality. While the results of this study are limited based on sample size and limited quantitative analysis, it is important in emphasizing the importance of faculty in LA adoption initiatives by institutions of higher education. Also, the results reveal a critical area of focus in our current study by reiterating "big brother" concerns among faculty, with the "misuse of aggregate results as it relates to faculty performance" (Bollenback & Glassman, 2018, p. 77). In closing and associated with previous mention of action research and DDDM, the authors suggest that "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” (Bollenback & Glassman, 2018, p. 75).

Rehrey et al. (2019) continued this line of research by determining the effectiveness of an LA program and the impact it had with engaging faculty, further emphasizing that “Faculty, with their knowledge of students and programs as well as their research expertise, are well-positioned to advance LA efforts on our campuses” (Rehrey et al., 2019, p. 86). The primary focus of this study lies within the development of the Learning Analytics Fellows Program (LAFP), where the purpose of LAFP is to “build LA capacity around an innovative (and successful) faculty learning community already predisposed to improve teaching, learning, and student success” (Cox, 2017; Rehrey et al., 2019, p. 87). Justification for this program is ultimately tied to a few specific elements, where faculty are situated in a place to advance the initiative through their perspectives on student experience as teachers, and the critical role faculty play in implementing LA strategies on their campuses. The structure of the LAFP was centralized in a faculty community of practice, where they would work together to solve problems and address challenges related to student success while sharing their results.

The LAFP engaged faculty in a cyclical process, where after an application process the fellows worked with colleagues to engage in a cycle of steps: viewing the data, identify research questions, submit proposals, collaborate in LAFP, disseminate results, and generate new questions. Moreover, when fellows are admitted they are provided with a significant amount of student data which includes historical, demographic, and performance data. The primary questions established and tested by faculty fellows were centered upon student success, which were categorized into four categories of choice, persistence, preparation, and performance (Rehrey et al., 2019, p. 90). Data collection from participating LAFP faculty were collected in surveys and interviews, where the surveys were comprised of 10 Likert scale items centered upon faculty sense of engagement in student success, utilization of learning analytical data, and community belonging for student success.

Quantitative phase results found that, overall, 64.7% of faculty believed their experience in LAFP would result in changes to their teaching and learning approaches, 82.4% agreed that using student learning analytical data was valuable when compared to pre-LAFP experiences, and 73.5% of faculty agreed that working with student learning analytics data increased the chance that their departments would use data to inform decisions. There was however a high degree of neutrality when the question was posed surrounding departmental or administrative decisions on the basis of student learning analytics research, where only 41.1% of faculty agreed.

Qualitative results revealed an overall increased faculty identity with ownership and responsibility for student success by participating in the LAFP program. One of the key qualitative results was centered upon data-driven decisions in specific programs, "Because of the research we have conducted, I have a lot more confidence about our programs… it's much better than being vague and saying we offer this class and think it helps" (Rehrey et al., 2019, p. 92). Even though the results of this study were preliminary, it is important in the development of a program that will increase faculty engagement with LA practices, with a majority of faculty in the LAFP program indicating that it helped them to feel a sense of belonging and commitment to student success in their programs.

College campuses have a variety of stakeholders, especially within the context of LA (Sun et al., 2019). Parrish and Richman (2019) emphasize this point in their review of literature on multiple stakeholder experiences in LA with a particular emphasis on university administrators and faculty perspectives. In the initial review of literature, the authors of this study point out there while research surrounding LA was a growing area, it was rather narrow in specific areas, particularly in improving student success outcomes, academic performance, and knowledge acquisition (Viberg et al., 2018). The study goes on to highlight Svinicki et al.'s (2016) work that found self-efficacy in data collection and analysis to be a critical factor in faculty participation in the LA process, and an important element where "whether a faculty member utilized available data was largely dependent on his or her beliefs as to its benefits" (Parrish & Richman, 2019, p. 6). Additionally, studies by Howell et al. (2017) and Kahn (2017) are accentuated as they also focused on faculty perceptions through a qualitative methodology.

Supplementary studies on faculty concerns regarding data utilization in LA are also mentioned, where Knight et al. (2016) emphasized faculty caution for data utilization if it could potentially stereotype students into "good" or "bad" student classifications, along with West et al.'s (2016) study that identified faculty concerns related to the ethical operation of student data. The authors proceed to describe the role of faculty member's responsibilities when engaging with LA, specifically "faculty members engaged in data-based decision making using the adopted LMS, academic management systems (AMS) or direct observations of student's performance" (Parrish & Richman, 2019, p. 10). Moreover, program coordinators are frequently accessing course evaluations of faculty and student performance data housed within LMS platforms. This study highlights as well that many institutions of higher education are in similar spaces in the adoption and implementation of LA initiatives at their institutions, however, as posited by Ifenthaler (2017) many institutions were identified as underprepared based on staff training or resources to support LA.

While previous literature had begun to emphasize faculty perceptions of LA, an increasing area of interest is how and why faculty adopt LA practices in their courses. In another qualitative study, Arthars and Liu (2020) interviewed creators and users of an LA platform called the Student Relationship Engagement System (SRES). The authors highlight that faculty (i.e., teachers) actions are critical to the success of LA, "even though there have been relatively few studies that analyze their perspectives in terms of LA adoption and implementation" (Arthars & Liu, p. 2). Moreover, previous studies have established that faculty who used LA platforms indicated that compatibility with pedagogical practice and needs were important elements in acceptance, and that successful LA practices relied upon individuals within their specific organizational structures (Dawson et al., 2018; Herodotou, 2019a).

The authors proceed to explain that faculty adoption of LA has been focused primarily in two theoretical frameworks with Davis' (1989) Technology Acceptance Model (TAM) and Ali et al.'s (2013) Learning Analytics Acceptance model (LAAM). The LAAM was developed to better understand teachers' perceptions of and usability of LA tools, and more so teachers' intentions to adopt it and understand the value of the analytics being supplied. Surprisingly, as the authors point out, ease of use and utility (i.e., usefulness) were not significant factors for educators to display behavioral intention to adopt LA tools in their teaching (Ali et al., 2013, p. 140; Arthars & Liu, p. 3). The SRES platform utilized an early warning system where teachers could use course data to personalize emails to subsets of students, and the platform also allowed teachers the ability to populate data which they deemed relevant in their specific context. Results from the study found that the flexibility of the SRES system did positively affect teachers' perceptions of the platforms advantages, but it did also negatively influence perceptions of platform complexity. Moreover, the authors note an ongoing challenge to realize teacher and student benefits in utilizing LA, and through Rogers (2003) Diffusion of Innovations framework the authors hope to expand upon previously established approaches in the TAM and

LAAM to understand educator perceptions and adoption of LA practices in their courses. Conclusively, Arthars and Liu (2020) point out that "it is also crucial that LA systems are flexible in accommodating for a wide variety of need and applications, considering the diversity of learning and teaching contexts and the educators and students in them" (Arthars & Liu, 2020, p. 15).

Faculty Course Data, Surveillance, Privacy and Trust

In another study utilizing a case study approach, Brown (2020) analyzed the perceptions and practices of physics faculty members and their interaction with an LA dashboard. The adoption of these dashboards involved an active learning approach known as "peer instruction," where the "PI engages students during class through activities that require each student to apply the core concepts being presented and then explain those concepts to their fellow students" (Brown, 2020, p. 388; Crouch & Mazur, 2001, p. 970). Brown elaborates that this approach of data-informed teaching was not a new phenomenon, and that there are a multitude of factors that influence this data utilization including social networks and organizational policies. The core component of this study was instructors' utilization of LA dashboards, which "allow users to view and explore information within a personalized display that aggregates(s) different indicators about learner(s), learning processes and/or learning context(s) into one or multiple visualizations" (Brown, 2020, p. 386).

The author's data collection involved observations of faculty instruction and departmental meetings, which also included the collection of classroom artifacts and instructor interviews. Instructor interviews were conducted at the start of the semester, after completion of the first exam, and once the semester had ended with a semi-structured interview protocol. Results indicated LA dashboards filled a variety of roles throughout the semester, notably with minimal utilization by instructors during class and further use during office hours. Two primary concerns were identified as well with the LA dashboard's data consumption requests for more course resources to create trace data, and how the LA dashboards were being used by institutional agents to "surveille their activities" (Brown, 2020, p. 391). Further elaboration is warranted with two of the study's primary themes. First, instructors indicated that they utilized the LA dashboards for out-of-class interactions more than in-class sessions. Instructors also reported that lacking data clarity was a point of determent, additionally with concerns about the quality and validity of the data being gathered and presented in the dashboard. This concern with data quality and validity was tied to classroom "clickers" where students would interact with content of the course by participating with a digital device. However, the author observed, and instructors indicated that students were often handing clickers off to other students who participated for them when they were not in attendance, "I don't trust the numbers. I think [students] show up with a correct response, but they did not actually-they are not there" (Brown, 2020, p. 393).

Finally, a theme which resulted focused specifically on faculty perceptions and concerns as it related to surveillance of instructional activities. The study indicates that many of the instructors who utilized LA dashboards were not comfortable with how the data was dispersed, which generated conversation on instructional strategy and instructor's classrooms. One specific example involved a department meeting where an instructor had to explain what appeared to be low attendance, which was ultimately informed by a no-required attendance policy. Additionally, concerns over predictive analytic tools caused one instructor to remove the LA dashboard from the courses' LMS to prevent "unwelcome surveillance" (Brown, 2020, p. 395). This was a critical point of observation in the results, where the concern over instructor surveillance was common. When the author informed faculty that course data from students was being used for the training of prediction models centered upon retention, a concern arose among the participating faculty, “their primary concern was that they as instructors are not identifiable in the research, especially when results were shared internally” (Brown, 2020, p. 395). The results of this study are significant in that they contribute to the collective research surrounding faculty perceptions and utilization of LA, but more so that it revealed additional concern among participating faculty that their data was being tracked. Moreover, the data being tracked could be linked to internal initiatives or model training that could be linked to their courses and instructor performance, where instructors had some expectation about their autonomy as it related to their courses (Brown, 2020, p. 396). In closing, the author notes that “while an increasing body of institutional policies speak to how, when, and where student data can be collected and analyzed, it seems as though few policies exist to delineates the rights of instructors as data subjects or data citizens” (Brown, 2020, p. 397).

Expanding upon faculty encounters and perspectives of LA, Li et al. (2021) in a qualitative study looked to expand upon the process that instructors engage with to utilize analytics in their teaching practices beyond initial interactions with LA tools. Thematic analysis revealed that faculty formed a series of questions that related to their process of engaging with analytics. In one example, faculty posed “problem-oriented” questions, which related to content engagement or specific students or student subgroups where faculty may be able to identify students who were struggling or missing work to compare with other students. In other words, a potential comparison between high-performing and low-performing students, where instructors could “encourage [low-performing] students to exhibit similar behaviors to see if that might increase their engagement with the class” (Li et al., 2021, p. 348).

Challenges also became apparent for faculty in their sense-making of using analytics in their courses. Examples include difficult navigation of the dashboards/data, lacking information on what data was being collected, and ultimately the usefulness of the data for actionable changes in course, “I couldn’t make sense of a lot of this information. I just wanted to see what are the most opened files and where people are going to the most” (Li et al., 2021, p. 350). In closing, the authors note that instructor utilization of LA in their courses is often associated with data-driven decision making, but it was more appropriate, based on their results, to incorporate LA as an expansion of practices which instructors were already utilizing through observations and student artifacts. Additionally, Li et al.’s results promote the idea that additional support is needed to inform faculty on analytic tools and processes, through workshops or coaching, that “go beyond the basic showcase of how to navigate the analytics, to demonstrate the full loop from question to insight to action” (Li et al., 2021, p. 352).

Over time, research on faculty perceptions and utilization of LA has begun to spotlight specific characteristics of faculty data and privacy in how it shapes perceptions of LA in their classrooms. In a study by Jones et al. (2021), the growth of LA tools is highlighted as commonplace in educational technology, however, limited research is focused on faculty perceptions of their privacy or the privacy of their students. In a survey of 500 full-time higher education instructors that focused on perceptions of privacy for faculty and students, privacy was an important component of behavior and learning. The authors note in their review of literature that while students are usually the primary subjects of LA research, faculty are the “primary users, as they are the ones that utilize data and dashboards to effect instructional change and intervene with students” (Jones et al., 2021, p. 1529). With that said, limited studies have focused on faculty perspectives in LA, and are ultimately under-researched especially within the context of faculty or student privacy.

As posited in the previous section of this literature review, the authors of this study note that ethical and privacy issues in LA are a significant area of concern. Reflecting on the utilization of LA and dashboards in instruction, Jones et al. go on to highlight the emerging area of LA literature related to issues regarding faculty, “the surveillant eye of learning analytics easily turns to faculty who are themselves embedded in and reliant upon institutional information infrastructures like their students” (Jones et al., 2021, p. 1530). This next point is critical, as Jones et al., note that thus far faculty have retained academic freedom to make instructional choices, however, “increasing surveillance and decreasing faculty power potentially make these institutional actors subject to invasive management and autonomy-limiting digital governance” (Jones et al., 2021, p. 1530). Notably, LA researchers have called for LA methods and measures to not be used against faculty (Hall, 2016; Jones et al., 2021), but changes with institutional administration in higher education involving audit culture and restructuring can have real implications, especially in the context of data-driven decision-making (Jones et al., 2021; Morozov, 2013; Selwyn & Gašević, 2020).

The authors continue to unpack LA research regarding faculty, which has been primarily focused on faculty adoption of LA tools and data-driven decision making (Arthars & Liu, 2020; Bollenback & Glassman, 2018; Dietz-Uhler & Hurn, 2013; Hora et al., 2017), within these studies however is an emerging area of privacy concerns. Moreover, faculty perceptions of LA have indicated a “big brother” or “surveillance” component, more specified within Parrish and Richman’s (2020) study which found that faculty were aware of LA in the context of academic freedom being reduced over time. These issues concerning faculty privacy and perceptions of LA were the basis of two primary research questions, both of which centered on faculty value of their own privacy, and their student's privacy. Through quantitative methodology, Jones et al.'s study revealed a significant series of results that relate to faculty perceptions of LA and their own privacy. Faculty ranked definitions of privacy as it related to their perceptions and utilization of LA, where the majority of faculty indicated that information access was the most prevalent, followed by personal privacy. In other words, privacy regarding the flow of information in a given context such as an educational institution, and personal privacy related to a faculty member's dignity, autonomy, and independence were the predominate areas of resonation. This study is important as it is one of the first to attempt unpacking faculty concerns of "surveillance" and "big brother" elements of LA by understanding the role of privacy inherent in this area of research.

One of the most recent studies to focus on faculty and instructor perceptions of LA was conducted by Tsai et al. (2021), and expanded upon the element of distrust and trustworthiness of LA. Through a mixed-methodological approach survey and focus group data explored expectations of LA while factoring in distrust and the implementation of LA. The authors note that while the potential benefits of LA are apparent, there are a variety of challenges and issues that need to be addressed further with respect to individual perceptions and utilization. Specifically, "The values and beliefs held by individuals shape people's perceptions and interpretations derived from data, their motivations to engage with data, and their inclination to act on information derived from data" (Tsai et al., 2021, p. 82). Notably, the adoption of LA lies within individual levels of trust, as previously established by Drachsler and Greller's (2016) study in the DELICATE checklist to promote trust in LA implementation. This notion of trust as it relates to LA, while not explicitly done previously with respect to faculty, has developed in part due to prevailing trends in higher education. Tsai et al. (2021) point out societal and market trends have influenced the education sector to "provide evidence to demonstrate quality and excellence to funding bodies and the public" (Tsai et al., p.83). Resulting from this is the drive and emphasis for institutions to adopt LA in order to enhance performance in quality metrics which include teaching, student outcomes, student satisfaction, post-graduation employment, and student outcomes of learning (Tsai, Rates et al., 2020).

The authors go one to propose two primary issues as it relates to the trustworthiness associated with LA: the subjectivity of numbers, and the fear of diminutive power. Unpacking the first issue, insights gained from LA processes and data are ultimately objective, where significant effort goes into the standardization and processing of data for analysis (Jovanovic et al., 2007; Slade & Prinsloo, 2013), and the sources of LA data are typically centered upon trace data (Tsai, Rates, 2020; Tsai et al., 2021). Within this context, the subject of observation also plays an important role in shaping behavior and engagement with data, where being observed can influence behavior that informs algorithms (Brown, 2020). While data-driven decision making is also a prevalent theme within the literature on faculty perceptions and adoption of LA, it can also act as a source of mistrust (Howell et al., 2018).

Within the second issue, the fear of power diminution, the components of distrust lie in a variety of areas which include data extraction as a form of control when data collection is purposed within prediction or modification of behavior (Zuboff, 2015). Notably, with respect to faculty (i.e., academic staff), there is a degree of vulnerability in losing academic autonomy if LA initiatives or data collection are being utilized to judge teaching performance or shape teaching strategies for measurable outcomes (Brown, 2020; Kwet & Prinsloo, 2020; Selwyn, 2020). Ultimately, the authors note that "the issue of power distribution among different stakeholders in an educational environment is an important aspect to consider when defining data control, stakeholder responsibility, and accountability" (Tsai et al., 2021, p. 84). It is worth mentioning as well that there are multiple efforts to establish co-design models in LA initiatives, such as Chen and Zhu's (2019) process for designing LA systems, and four primary recommendations from Holstein et al. (2019) which include evaluating stakeholder needs and connecting real world scenarios of teachers to analytics processes.

The results of this mixed methods study focused on a sample of 81 teaching staff (i.e., faculty) in the UK, and found that overall teaching staff indicate high trust in receiving guidance on LA access about students, as well as a "strong belief that LA would be used to update students about their progress, and that the university should and would have an ethics and privacy protection in place" (Tsai et al., 2021, p. 93). However, there were a variety of trust issues that became apparent in both phases of analysis which included concerns of data accuracy, professional autonomy, interpretability and ease of use, and teaching staff workload. With respect to LA data, teaching staff had a low overall level of trust in the data being accurate and associated it with the discouragement of behavior and discounting of other variables in learning processes. With respect to faculty professional autonomy, there was a general negative sense towards obligation to act on LA results, but also indicated a positive belief that they would have the obligation imposed upon them regardless. Teaching staff sense of distrust was also very prevalent in LA being used for performance evaluation/judgment. Finally, another area of distrust among teaching staff pertained to workloads, especially with LA being interpretable or easy to use, as well as potentially demotivating effects that could be had on students. Overall, the study found that matters of trust and distrust among teaching staff were a factor in considering political and social factors in LA adoption and utilization by universities.

In summary, faculty perceptions and utilization of LA is a relatively new area of research that focused initially on general perceptions of LA to support student learning outcomes, understanding which faculty utilized the data, and how interactions with specific elements such as LA dashboards were beneficial or difficult. Over time, this line of research has developed into more specific elements of faculty perceptions and utilization as it pertains to LA accessibility and ease of use, validity and accuracy of LA data, faculty privacy and trust, and specific perceptions centered around the proposed benefits of LA including intervention and improved or measurable learning outcomes.

Faculty Trust in Learning Analytics

Literature centered upon perceptions of faculty trust in LA and course data is limited. What becomes apparent in the review of LA literature however is that the theme of trust is reoccurring in not only the perceptions of faculty in LA, but with multiple stakeholders and their engagement with LA initiatives or practices at institutions of higher education. Trust in the field of LA research is a critical component in fostering LA initiatives and online platforms (Pardo & Siemens, 2014), establishing data privacy and LA quality (Scheffel et al., 2014), faculty perceptions of data quality (Brown, 2020), existing distrust of LA (Tsai et al., 2021), data-driven decision making (Howell et al., 2018), student issues of trust and privacy concerns (Jones et al., 2019; Mutimukwe et al., 2022), and faculty trust of multiple stakeholders in LA (Alzahrani et al., 2023).

Issues of trust are often associated with ethics and privacy issues in LA, where concerns over data privacy and ethics are commonly cited in LA literature (Attaran et al., 2018; Banihashem et al., 2018; Bollenback & Glassman, 2018; Ifenthaler & Tracey, 2016). However, this line of research has primarily focused on interests of students' privacy of data and trust as it pertains to their data (Jones et al., 2019; Ifenthaler & Schumacher, 2016; Prinsloo & Slade, 2015). Jones et al. (2019) elaborated on the trend of ethical research focusing on students, and that ultimately faculty perspectives are not a frequently studied topic. The authors highlight that while some research has focused on faculty adoption of LA, privacy issues have arisen in the process. The two primary examples being student profiling, where faculty indicate concerns regarding bias and potentially incorrect actions in the student learning process, the second being latent implications regarding academic freedom posited by Parrish and Richman (2020).

Faculty Trust

Focusing on the role of trust for faculty members, Shoho and Smith (2004) were some of the first researchers to address the role that trust plays within this important population. The study begins by emphasizing a shift in the 1980s and 1990s with public distrust as it relates to businesses and politicians, and transitions to the importance of trust in organizational effectiveness. Moreover, in what initially began as an area of emphasis among economics and psychologists, trust was eventually found to be a critical component of healthy school environments. Specifically, “Faculty trust represents a critical component of educational organizations, one that may well affect student academic performance, faculty efficacy, and institutional health” (Shoho & Smith, 2004, p. 280). The purpose of their study was two-fold in addressing a gap in literature pertaining to faculty trust, as well as a definition and measure of higher education faculty trust at the organizational level.

While previous literature addressing the conceptualization and definition of trust is broad, the authors utilized Hoy and Tschannen-Moran’s (1999) definition of trust, where trust is “an individual’s or groups willingness to be vulnerable to another party based on the confidence that the latter party is benevolent, reliable, competent, honest, and open” (Hoy & Tschannen-Moran, 1999; Shoho & Smith, 2004, p. 281). The primary goal of the study was the establishment of measures for faculty trust as it relates to institutional stakeholders, including colleagues, deans, and students. Upon completion of exploratory factor analysis and component analysis three factors were identified within this study; Collegial trust, which focused primarily on the trust established between colleagues, student trust (i.e., how faculty members trust their students), and trust in the dean for each faculty members respective college. Each measure displayed a Cronbach's Alpha reliability of greater than .80, and were positively correlated, resulting in the establishment of the Higher Education Faculty Trust Inventory (HEFTI). Worth mentioning as well is that ANOVA results revealed there were statistically significant differences among faculty academic ranks in collegial trust, where adjuncts and assistant professors indicated higher levels than those of full and tenured professors, with similar results in trust with a faculty member's dean. Notably, academic rank did not affect perceptions of student trust, and there were no statistically significant differences between men and women in their three categories of trust. In closing, the authors note that "As colleges and universities continue to reflect the promise of greater stakeholder involvement, the saliency of trust in higher education will need to be further probed and examined" (Shoho & Smith, 2004, p. 292). This is an important sentiment to carry over into the focus on the role of faculty trust in perceptions and adoption of LA in their courses, as the theme of multiple stakeholders is a frequent component to the successful adoption and implementation of LA initiatives (Gasevic et al., 2016; Greller & Drachsler, 2012; Reyes, 2015; Wasson & Hanen, 2015).

Student Trust and Learning Analytics

While the theme of trust is mentioned periodically in the establishment and growth of literature on perceptions and adoption of LA initiatives, Drachsler and Greller's (2016) study on the role of trust in LA initiatives was one of the first. The authors note that transparency and trust are critical components for data subjects, highlighting the practices of private companies like Google, who “keep their algorithms secret, and, yet, as long as results are relevant and in line with users’ expectations, there is trust in the service, despite it being a black box” (Drachsler & Greller, 2016, p. 95). The development of an eight-point checklist named DELICATE was the result of extensive reviews of literature and workshops to establish a system for “trusted learning analytics” (Drachsler & Greller, p. 96). Ultimately, DELICATE was created to establish a level of trust between stakeholders and LA initiatives, focusing more on regulations and going beyond legal requirements to increase the trust of stakeholders. This is a very important concept based on the suggestions of the authors, where “In order to establish this level of ‘trust’, regulations need to be in place that guards the personal information rights but also empowers the organization to gain insights for its improvement” (Drachsler & Greller, 2016, p. 96).

While Drachsler and Greller’s (2016) work emphasizes the role of trust in successful LA implementation for institutions, Jones et al.’s (2019) analysis of trust as it relates to students in LA and data mining practices expands upon this concept. Specifically, trust is a vital component between students and their institutions of higher education, this is especially relevant in not only the utilization of academic and course data, but potential surveillance data that institutions use to track student activity. This study is also one of the first to introduce the role of the Family Educational Rights and Privacy Acts (FERPA) into discussion of student data mining and LA practices, noting that it provides institutions complete authority over data collection, retention, and use, and ultimately these institutions “enjoy incredible leverage in deciding what data are protected by FERPA and what are not” (Jones et al., 2016, p. 1236). Based on their review of cases, the authors emphasize that trust is an important component between students and institutions of higher education, “HEI’s have a moral obligation to act in students’ interests, and that LA surfaces such an obligation in ways other socio-technical systems have not” (Jones et al., 2016, p. 1237).

Mutimukwe et al.’s (2022) research expands upon the role of trust and privacy in LA model development and is one of the first studies to quantitatively measure trusting beliefs among students. The primary goal of the study was the development and validation of the Students’ Privacy Concerns (SPICE) model which incorporates perceptions of privacy risks, privacy control, and trusting beliefs. Earlier, trust was defined by Shoho & Smith (2004) as a broader concept, where Mutimukwe et al. (2022) propose trusting beliefs, which are “the degree to which higher education institutions are dependable in protecting users’ (e.g., students’) personal information” (Malhotra et al., 2004; Mutimukwe et al., 2022, p. 936; Pavlou & Fygenson, 2006). The development and validation of SPICE was the primary goal of this study, and the results ultimately found that “students’ perceptions of privacy risks in LA practices are a determinant factor of their privacy concerns” (Mutimukwe et al., 2022, p. 944), which ultimately influenced their trusting beliefs among other factors, which has the potential to influence a distrust in how institutions of higher education collect, analyze, and store LA based data. These results and item validation informed the adapted measures of faculty trust and course data control utilized in the current study.

Faculty Trust and Learning Analytics

While the concept of trust is gaining more traction for students and the LA practices of higher education institutions, empirical approaches to understanding faculty trust in LA have been exceptionally limited. However, the most recent study by Alzahrani et al. (2023) specifically examined teaching staff trust in LA stakeholders and tools in higher education institutions. The study opens by highlighting the role of trust in technology adoption among faculty members, emphasizing however that the role of trust in the adoption of LA in institutions of higher education has ultimately not been examined in detail. Through a mixed methodology approach the primary goal of the study was to explore teaching staff trust of LA stakeholders, which included higher education institutions or third parties and LA technology. Additionally, the study hoped to better understand additional factors that could hinder or enable LA adoption.

The role of trust in LA, while under-investigated, is again pointed out as a component or theme in previous studies of LA, which is problematic when the utilization of LA can help to inform data-driven decision making and improve educational processes. Initially, trust in technology was one of the first areas to garner further study with the growth of Web 2.0 and the adoption of LMS platforms by higher education institutions, along with practices in academic analytics and data mining. Establishing a foundation of literature, the authors note that various studies have identified levels of trust as important in their utilization of technology and perceptions of their institutions (Li et al., 2012; Montaque et al., 2010; Muir, 1994).

Alzahrani et al. (2023) provides further elaboration on the limited theme of trust in LA, primarily where trust research is typically focused on sub-groups of stakeholders, and a review of the literature notes that the role of trust in LA can be classified in two categories, trust in stakeholders, and trust in LA tools. The review of literature reveals that university trust plays a pivotal role in positively influencing teaching staff decisions to use LA tools (Klein et al., 2019; Tsai et al., 2021), where the current study focuses primarily on the populations of administrators and management, as well as third-party technology vendors (i.e., those who provide and support LMS systems, LA services, etc.). Additionally trust in LA tools for data-driven decision making are another important area of LA adoption (Egetenmeier & Hommel, 2020). However, existing literature on trust and LA tools has been primarily focused on concerns of data quality (Klein et al., 2019), lacking integration and utility of LA tools (Arnold et al., 2014; Norris & Baer, 2013), and lacking training or data literacy with LA tools and course data (Amida et al., 2022).

Analysis of survey and interview data from teaching staff at higher education institutions in Saudi Arabia utilized measures related to faculty trust and LA usage in a comparison of what users' ideal expectations were to predicted expectations of what happens in reality. Results indicated a series of significant results; First, teaching staff indicated high degrees of trust towards LA stakeholders in areas of "access", "allowing students to make decisions", and "understanding student performance" (Alzahrani et al., 2023, p. 18). However, perceptions of distrust towards higher education institutions were revealed in lacking consensus of staff capabilities, and concerns related to loss of professional autonomy. The authors note that these results are significant in supporting previous research such as Alsheikh's (2019) study that found institutional competence to be a significant factor considered in LA adoption, while also contributing new information by "indicating that teaching staff's trust in HEIs competence may relate to their experience with the current HEI's technology infrastructure or the experience and capacity of HEI's in data analysis" (Alzahrani et al., 2023, pp. 18-19).

With respect to teaching staff distrust of third-party entities, data ownership was another area of concern which aligned with the results of (Leitner et al., 2018), and additional concern was associated with third parties lacking context or situational information about the situation of higher education institutions. Therefore, the authors suggest that supporting trust of teaching staff is a critical area for third-party platforms, and ultimately garners a competitive advantage in a comparison of other LMS or technology platforms. Finally, an additional result of this study found that teaching staff "had a high level of trust in the usefulness of LA as a tool to improve the educational experience in general to achieve the HERI objectives" (Alzahrani et al., 2023, p. 21). Overall, the study concludes by suggesting trust should be considered in LA practices and results in different outcomes based on the type of stakeholders being engaged (e.g., higher education institutions, third-party platforms). Moreover, "Given the importance of trust for the success of LA adoption, HEIs should prioritize the teaching staff's trust in LA through actions to better serve the goals of teaching staff as primary stakeholders in LA" (Alzahrani et al., 2023, p. 21).

Course Data Control

Literature addressing faculty utilization of course data and perceived "control" of that data are limited. Frequently, when data ownership is contextualized within higher education, and LA specifically, it is often associated with student stakeholder's sense of trust with an institution (Mutimukwe, 2022; Pardo & Siemens, 2014). Moreover, the sentiment remains for students as to why they should trust an institution to utilize their data to potentially improve their experiences and serve their interests (Jones et al., 2020). Intellectual property and privacy concerns have also been accentuated in previous studies as it relates to faculty, especially in the context of self-designed course materials. The primary theme being a degree of ambiguity on whether faculty course materials are considered intellectual property, and moreover who owns course related intellectual property (Dennen, 2016).

Previous studies have identified that some faculty do view their syllabi and other materials as proprietary products (Greenhow & Gleason, 2015), but there does not appear to be any existing studies which have looked at the data being collected in courses as it relates to faculty sense of ownership or control. Gadd and Weedon's (2017) content analysis addresses the literature surrounding ownership of e-learning and teaching materials in relation to policy development for universities in the UK. While the existing studies have focused primarily on copyright permissions of e-learning materials (Halme & Somervuori, 2012), and the ability to re-use content via licensing (Cheverie, 2013), there is very limited literature surrounding the ownership of academic's e-learning materials that they produce. With the advancements of Web 2.0 and the growth of MOOCs and LMS platform utilization for big data collection in higher education, the debate surrounding ownership of teaching materials has garnered increasing attention (Gadd & Weedon, 2017). While this study does highlight the issue in the UK, the authors emphasize that this is a global issue with respect to legal considerations surrounding copyright and ownership of course materials. The results of Gadd and Weedon's (2017) content analysis found that in the majority of cases UK university copyright policies "state that the ownership of both internal and distance or e-learning materials rests with the university" (Gadd & Weedon, 2017, p. 3246). Concerningly, the concept of shared ownership for academic staff as argued for by Davies (2015), is scarce in such policies in the UK, with only 14% of the policies analyzed offering some form of shared-ownership for e-learning materials.

In a more general societal perspective, our sense of control as it relates to data and personal information is gathering further attention. Auxier et al. (Pew Research Center; 2019) emphasized this point in a survey by the Pew Research Center, which found that the majority of Americans indicate that they have little control of their data collected by companies and the government. Interestingly, when the same sample was asked about what they understood about data the government collects 78% said they had very little or no understanding of what the government does with the data, with 59% indicating the same about companies. While data collection by the government is a separate issue in many ways than the collection of course data, these survey results could provide clues as to how perceptions of data control translate into higher education, and more specifically how faculty perceive their sense of ownership and control over the data being collected in their courses. As mentioned previously in this review, sense of trust is often associated with control in studies concerning ethics and privacy for LA practices and initiatives. Specifically, the low levels of understanding among those respondents links up with the results of Amida et al. (2022), where faculty reported a lack of training or competency to work with the data as a concern or challenge, a prevailing trend in LA research focused on faculty members (Tsai & Gasevic, 2017; Wasson & Hansen; 2015).

As previously established, studies have rarely focused on the concept of “control” within the context of LA, this is especially rare within the element of course data control in how the university collects, analyzes, and stores such data. However, “control” is a common theme in discussions of data ethics and privacy, as well as data ownership. This is prevalent in Asswad and Gómez’s (2021) definition of data ownership as “the possession of complete *control* over the data and its rights, including the right to grant rights over the data to others” (Asswad & Gómez, 2021, p. 1). Svinicki et al.’s (2016) study focusing on factors that influence faculty utilization of course data for improved instruction emphasized faculty member’s autonomy or sense of control in task engagement for student data collection and utilization. Similarly, in Tsai et al.’s (2021) study, two primary issues in trustworthiness of LA included faculty concern for power diminution, which included a component of data control and the purpose of the data being collected for potential behavior modification. Ferguson et al. (2019) in a review concerning the future of LA note that control is an area of consideration, both in control of analytics, learning processes, and data distribution among stakeholders; “Both learners and teachers need to be able to trust the people and systems that control their data, as well as the algorithms that are used to guide decisions about learning (Ferguson et al., 2019, p. 55).

Mutimukwe et al.'s (2022) study of student privacy concerns in LA as cited previously included both measures of trust and data control. The study emphasizes the point that control is a critical factor influencing privacy concerns. Notably, several privacy issues exist in understanding how stakeholders perceive or engage with LA, a central component of privacy concern being personal control over personal data (Botnevik, 2021). The authors propose a series of items related to student perceptions of data control as it relates to privacy control, defined as "the individual's beliefs in his/her ability to manage the release and dissemination of personal information" (Mutimukwe et al., 2022, p. 936; Xu et al., 2011). This is one of the first studies to implement such a measure in an attempt to address a critical area of LA research that has gone under-developed. Notably, Tsai et al. (2020) posit that "students fear losing control, especially when data is shared with external entities, and perceived risks are the major factors that may impact the offering of data to be used for LA" (Mutimukwe et al., 2022, p. 937; Tsai et al., 2020).

Additionally, Jones (2019) emphasizes that privacy-as-control of personal information is critical for autonomy in the LA setting, and when control is "not allowed or when the future use of information is unknown, individuals distrust organizations" (Mutimukwe et al., 2022, p. 939; Traddei & Contena, 2013). The results of this study supported the concept that privacy control was significant in trusting beliefs for institutions of higher education with respect to LA data. While this study does not directly measure perceptions of course data, privacy control and control as a measure of trust in the context of LA were an important driver of adapted measures for the current study.

Trust and Control with Faculty Performance Evaluation

An additional area to highlight as it relates to faculty trust and control in the context of LA is the prevailing sentiment of faculty concerns for LA and the potential utilization of course data for performance evaluation. This potential exists based on the mixed results of prior empirical study, where traditionally, course data for performance evaluation has been centered upon student evaluations of teaching (SET). SETs often take the form of paper or electronic surveys which are utilized by administrators to assess teaching practices, a process employed by universities to evaluate teaching competence and quality (Hornstein, 2017). These SET results are widely used by administrators for the evaluation process concerning tenure and promotion decisions (Abrami, 1990). While this practice is widely used across higher education institutions, it has drawn considerable criticism and skepticism of its value as a practice to not only improve student learning outcomes but assess the teaching performance of faculty for tenure and promotion decisions (Boring & Ottoboni, 2016; Hornstein, 2017; Wines & Lau, 2016). The question then becomes at what point does course data become a potential indicator of faculty performance? Moreover, what impact does institutional trust have on faculty motivation to then utilize LA in their courses to improve learning outcomes?

Bollenback and Glassman's (2018) study focused on faculty perceptions and adoption of LA and revealed in qualitative results that faculty were indeed concerned about the utilization of LA data for external purposes. Specifically, faculty reported concerns of how LA data could be used to potentially identify faculty as "bad" if students were not meeting learning objectives or similar criterium. Similarly, Tsai et al.'s (2021) study focused on teaching staff found that a critical area for distrust arose when LA could be used for performance evaluation.

The utilization of course data, academic analytics, data mining, and LA in potentially informing performance evaluation while limited in literature has been an area of exploration since the inception of LA as a field of study. Starting first with a study by Bermudez et al. (2011) which examined faculty performance based on data mining as an appropriate process utilizing clustering and regression analysis, notes that effective implementation would require more specified data collection efforts. Similarly, Mattingly et al. (2012) introduced the idea of academic analytics and LA being utilized for assessment practices, particularly with data collected from LMS platforms.

This initial trend of potential utilization of LA for teaching performance evaluation and assessment was addressed in Dringus' (2012) article on the potential harms of LA. Specifically, Dringus highlights concerns with data quality and interpretation, where data trails and activity had been centrally focused on students. However, in the context of instructors the question becomes "what is the visible and meaningful presence activity of the instructor and how is that data trail interpreted by administration as effective performance?" (Dringus, 2012, p. 93). This concern is also associated with changes outside of performance evaluation, with examples being changes to course loads and class size. With the concerns highlighted, the author also speaks to the potential benefit of LA in instructor self-reflection, answering questions related to feedback and course satisfaction considerations to become a better online instructor.

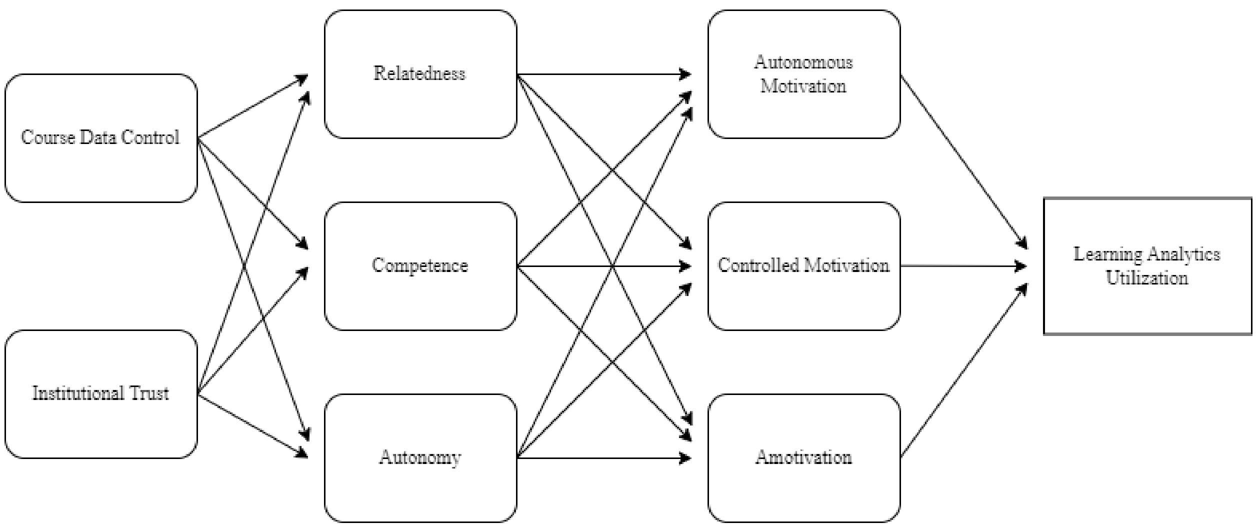
Within a few years of Dringus' (2012) article on concerns of LA data being interpreted by administration, one of the first pieces of literature to suggest administrative interest in potentially using LA for performance evaluation was published in Arroway et al.'s (2016) report on Learning Analytics in Higher Education. Initial survey and focus group results of EDUCAUSE institutions revealed that at the time, LA was still an interest rather than a majority priority for the majority of institutions, and that major challenges at the time included "data quality concerns, system-integration difficulties, lack of support of key leadership, and a possible faculty culture of resistance" (Arroway et al., 2016, p. 5). In unpacking this faculty resistance of culture, results also found that this could be due in part to questions surrounding faculty practices as they relate to student performance, "Faculty, already wary of and often resistant to measurement, may be suspicious of motives, data quality, and interpretation" (Arroway et al., 2016, p. 13). With this information in mind, a key measure of their survey involved institutional metrics of "faculty teaching performance," where "nearly a third (of institutions) indicated that they plan to use or are considering using learning analytics in student degree planning and faculty teaching performance evaluation" (Arroway et al., 2016, p. 18). The report concludes by emphasizing that at the time, LA's potential effect on faculty autonomy made it a politically challenging area.

Conceptual Framework

The current study examined the role of faculty trust with course data and their current university, perceived control of course data, basic psychological needs for LA, motivation for LA, and how those factors influence or predict faulty members' utilization of LA in their courses (see Figure 3). Overall, faculty members sense of control over course data and institutional trust with course data will have hypothesized direct relationships with basic psychological needs for LA, which share direct relationships with autonomous motivation, controlled motivation, and amotivation. While basic psychological needs for various tasks and behaviors share direct paths with autonomous motivation, this hypothesized model wanted to explore the role of psychological needs in both controlled motivation and amotivation. Finally, autonomous, controlled, and amotivation for LA share a direct path with LA utilization in faculty members courses, where autonomous motivation would be the healthiest and most self-determined predictor of LA utilization. Post-hoc analysis was also performed for modified model development based on the results of exploratory factor analysis, confirmatory factor analysis, and path analyses of the hypothesized model presented here.

Figure 3

Conceptual Framework of Control, Trust, Basic Psychological Needs, and Motivation on Faculty Learning Analytics Utilization



Note. Autonomous Motivation for LA is the combination of Intrinsic and Identified regulation types, whereas Controlled Motivation for LA is the combination of positively introjected, negatively introjected, and external regulation types.

Summary

This chapter reviewed the literature surrounding the early foundations of LA and its amalgamation of various combined disciplines including statistics and academic analytics. It also provides the basis of study for faculty motivation and its growing importance in recent years with changes to faculty members' teaching and research. Moreover, the chapter introduces the concept of course data control and highlights the importance of faculty trust in its relation to LA.

CHAPTER III

METHODOLOGY

The purpose of this study was to explore faculty motivation for learning analytics while introducing and testing perceived sense of control and trust as it relates to course data in LMS systems. Moreover, this study attempted to understand how these factors impact LA utilization in a faculty member's courses (see Figure 1). Ultimately, the study evaluated a model of faculty perceptions of course data control, trust as it relates to institutions and course data, basic psychological needs, and motivation types as predictors of LA utilization by university faculty. The overarching hypothesis was that faculty perceptions of control and external factors affecting utilization of course data would positively or negatively influence faculty motivation to predict LA utilization in their courses.

Research Questions

RQ1. What are faculty members' perceptions and practices related to course data control, institutional trust with course data, and learning analytics utilization?

RQ2. What differences exist among faculty with respect to autonomous motivation, controlled motivation, perceptions of performance evaluation, and the utilization of learning analytics in their courses?

> (H_1) There are statistically significant differences in levels of autonomous or controlled motivation, levels of concern regarding performance evaluation, or levels of learning analytics utilization based on teaching format, faculty rank, tenure status, Carnegie classification, or academic fields.

RQ3. What are the relationships among faculty course data control, institutional trust, basic psychological needs, motivation types, and learning analytics utilization?

(H_1) There are statistically significant relationships between measures of course data control, institutional trust, basic psychological needs, motivation types, and learning analytics utilization.

RQ4. What factors predict basic psychological needs for LA, motivation for LA, and learning analytics utilization in faculty members' courses?

(H_1) There are significant direct relationships between endogenous variables of motivation and the exogenous measure of learning analytics utilization in faculty members' courses.

Research Design

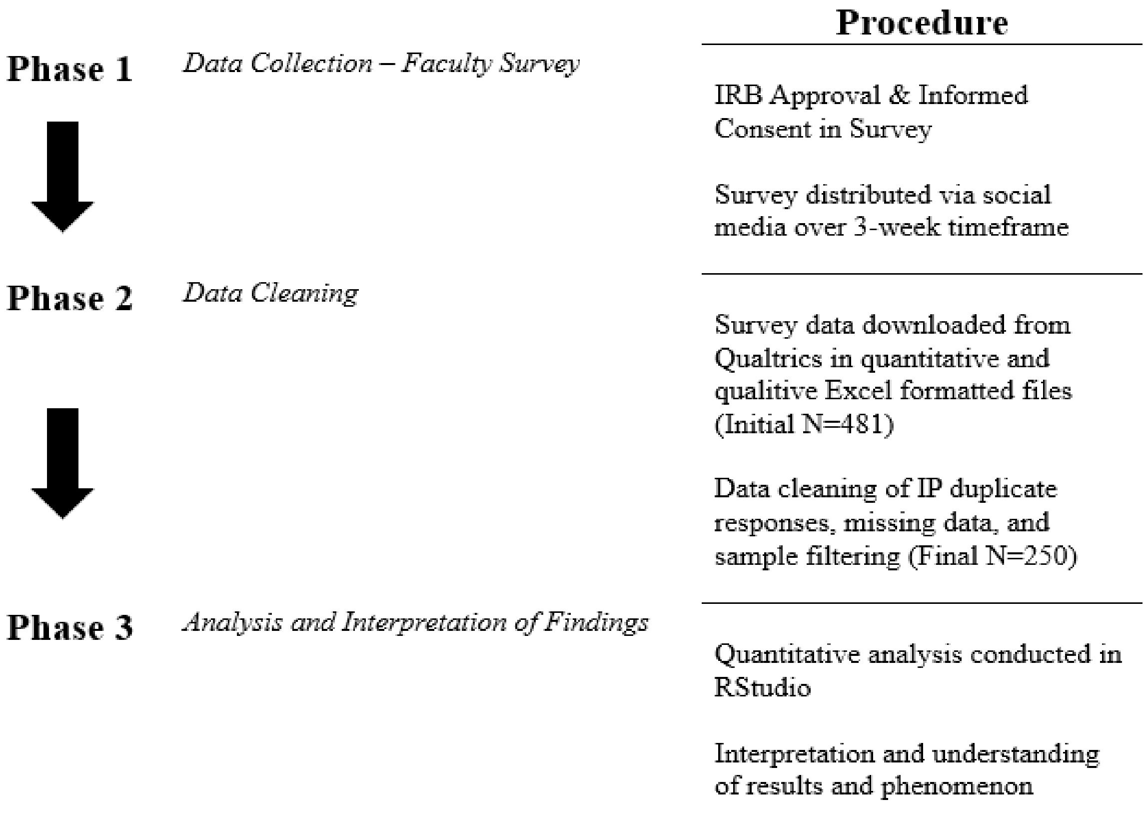
This dissertation employed a quantitative methodology approach to understand faculty members' motivation for LA while including factors in perceptions of course data control and institutional trust to utilize course data from LMS platforms. Survey development was carried out in two phases, first with a review of previous studies to adapt measures of faculty institutional trust, course data control, basic psychological needs for LA, motivation for LA, and finally utilization of LA by faculty members. Items were examined for face validity by a research group consisting of university faculty members and Ph.D. students, and the language was adjusted for three items due to technical terminologies. Preliminary analysis for this study utilized descriptive statistics and includes comparisons of faculty ranks and formats in analysis of variance (ANOVA). Multiple correlations were utilized for determining the potential relationships shared between control and trust items with motivation for learning analytics, and ultimately the implementation of specific learning analytics practices. Next, a confirmatory factor analysis (CFA) was utilized to test the measures of the study to inform the reliability of the data control and trust constructs, along with all other items. The primary analysis for these items/measures was completed through structural equation modeling (SEM), which is a collection of statistical techniques testing relationships between one or more independent variables on one or more dependent variables (i.e., endogenous, and exogenous; Ullman & Bentler, 2012). This method of analysis was utilized to answer in part the study's research questions by focusing on the potential relationships that exist between motivation types and faculty perceptions of LA, their motivation to utilize LA, and lastly their motivation for LA when controlling motivation by challenging external factors prevalent in the recent literature.

Participants and Procedure

In the current study, institutional review board (IRB#0005450; see Appendix A) ethical approval was obtained in February of 2023 proposing a quantitative study of higher education faculty recruited via social media. Study participants were recruited through social media platforms including Meta (i.e., Facebook) and Twitter, where a graphic/posting included survey links and a QR code inviting higher education faculty members to participate in a study which examines the factors impacting faculty motivation for teaching and research (see Appendix B). Specifically, higher education faculty members were asked to participate in a survey focused on their perceptions of innovations in teaching and research, which included separate sections on learning analytics, technology, and online mentorship (see Figure 4).

Figure 4

Data Collection, Data Cleaning, and Analysis Design



Survey access was opened in March of 2023, and data collection was completed in 21 days, with the recruitment message being shared approximately one to two times per week. The social media accounts which shared the posting for the survey had an estimated 500,000 followers combined. Upon survey completion, participants were invited to enter their e-mail addresses to be entered into a random drawing for one of (10) Amazon gift cards. In total, 492 survey responses were recorded.

Data collection was completed through the survey platform Qualtrics, which produced two Excel files containing both numeric and qualitative datasets. The data cleaning process was completed in Microsoft Excel and began with the filtering and removal of test survey responses prior to the start date of the survey being posted via social media. Next, duplication of IP addresses identified four repeat survey responses and were removed. Missing data were identified through an Excel formula; where missing data counts were utilized to create a variable where only those who had missing response totals suitable for analysis (i.e., filtering data for survey completion, where faculty had to complete 90% of items) were included in the final sample. With the removal of duplicate responses and missing data a sample of 354 was obtained which completed a majority of the survey items, resulting in a survey completion rate of 73.5% from the total collected survey responses of 481. The final step in data cleaning and sample selection involved the Carnegie classification and faculty contract variables, as the population of focus for this study was university faculty members who currently indicated some percentage of teaching in their contracts. Therefore, those participants indicating that their current higher education institution was classified as a baccalaureate, masters, or doctoral college/university, along with having some percentage of their contract dedicated to teaching, were selected for the final sample for analysis.

Study participants were 250 university or college professors, instructors, researchers, or analysts who indicated that their current higher education institution was a Carnegie classified baccalaureate college or university, master's degree granting college or university, professional or doctoral university, and high or very high research activity university (i.e., R1, R2). Faculty participants were majority women (71.9%), identified as primarily White (85.8%), evenly distributed in tenure status (i.e., tenured, on tenure-track, not on tenure track), and indicated some form of teaching as a percentage of their contract. It is worth further elaboration that the female faculty potential for overrepresentation is a potential effect on generalizability in the results and will be addressed in limitations.

Measures

Survey completion began with study information and informed consent based on the IRB protocol, where participants indicated consent for participation based on a skip logic question which granted access to the survey questions. Prior to participants beginning the LA specific measures of the survey, contextual information was provided in definitions of LA, LMS systems, and the inclusion of common examples of learning analytics practices:

Learning Analytics *is "the measurement, collection, analysis, and reporting of data about learners and their contexts, for the purposes of understanding and optimizing learning and the environments in which it occurs" (Society for Learning Analytics Research, 2011).*

Learning Management Systems (LMS)*, such as Blackboard, Canvas, Moodle, and D2L, collect data on student activity including the number of log-ins and minutes spent on activities, clicks and views of course content, and include a grade center.*

Common examples of learning analytics include:

1. Alerting students about their poor academic performance or engagement based on LMS data

2. Tracking student activity, participation, and progress data

3. Monitoring student performance through the grade center of your LMS

In total, faculty responded to 60 items measuring demographic and professional characteristics, current LA utilization, faculty control of course data, faculty institutional trust and course data, basic psychological needs for LA, and faculty motivation for LA. These items are included in the study codebook, see Appendix D.

Faculty Details

Participants responded to a series of items collecting demographic information which included gender, age, race, and ethnic identity. Additionally, faculty provided professional details which included their highest degree earned, academic rank, tenure status, academic field, Carnegie classification of their current institution, and their primary teaching format which included entirely in-person or online instruction (e.g., synchronous, asynchronous), and a mixture of both formats. The collection of information on faculty rank and tenure status are important for a couple of specific reasons as they pertain to LA research. Examples being where in technology adoption, Medlin (2001) posits that with respect to technology adoption "assistant or associate professors' work encompasses short-term priorities such as publishing or tenure pressures, whereas full professors' work encompasses consulting, entrepreneurial endeavors, advising, and possible increased involvement in administration" (Medlin, 2001, p. 28). Relating this to previously cited faculty challenges with LA in workload and cost-benefit considerations, professional status and rank are important considerations in attempting to understand how these classifications and statuses influence perceptions and utilization of LA practices.

Current Utilization of Learning Analytics

Faculty member's current utilization of LA was a primary construct measured in eight items adapted from Amida et al. (2022) that looked at faculty utilization of LA tools in their courses. The adaptation translates LA tools to general LA practices which faculty would engage with in their current courses. Faculty were asked to indicate how often they had done the following practices to utilize LA on a five-point Likert scale (1 = *Never*, 3 = *Sometimes*, 5 = *Always*). Example items included "Examined how students log-in data relates to their performance" and "Tracked the activity of students on discussion boards, blogs, wikis, etc.." Descriptive statistics for this measure, and all additional measures, are included in the results section (see Table 2).

Faculty Control of Course Data

The measure of faculty control as it relates to their course data was adapted from Mutimukwe et al. (2022) that focused on student privacy concerns which were used to shape faculty items in the current study. Faculty were prompted to indicate the extent to which they agreed with the following statements and responded to five items on a five-point Likert scale (1 = *Strongly disagree*, 3 = *Neutral*, 5 = *Strongly agree*) in a series of statements related to their sense of control with the data collected from their courses. Example items included "I get to decide if the data from my courses is shared with others" and a reverse coded item "My university owns the data from the courses I teach." Control and ownership of data in LA is a common theme which has been underdeveloped through quantitative methodology, especially from a faculty member perspective. This is one of the first studies to attempt measuring faculty perceptions as it relates to their control over their course data and items related to various institutional stakeholders (e.g., the university, colleagues).

Faculty Trust and Course Data

Faculty sense of trust as it pertains to course data was again adapted from Mutimukwe et al.'s (2022) study where items pertaining to trust were adapted from student perspectives to faculty. Faculty were provided a prompt stating "In regard to learning analytics data from your courses (e.g., tracked student activity, grades, content engagement, discussion board posts)" and responded to six items measured on a five-point Likert scale (1 = *Strongly disagree*, 3 = *Neutral*, 5 = *Strongly agree*) related to their general perceptions of trust and the data collected from their courses. Example items included "I trust that my university would tell the truth about the data" and a reverse coded item "I am concerned about my university using the data to evaluate my teaching performance." In total, two items were reverse coded in this construct, which acts as an attempt to measure the role of trust in a stakeholder (i.e., their university) and the data which is collected from the faculty member's courses. Trust is a common concern that appears in previous research pertaining to faculty perceptions and utilization of LA but has been underdeveloped in a quantitative approach.

Basic Psychological Needs for Learning Analytics

Measures of Deci and Ryan's (1985) Self-Determination Theory human basic psychological needs of autonomy, competency, and relatedness were adapted from Stupnisky et al.'s (2018) study of faculty motivation for teaching and best practices to focus on faculty perceptions of LA. Faculty were asked to respond to the following prompt, "Regarding learning analytics, to what extent do you agree with the following?" In total, four items for each basic psychological need resulted in 12 total items measured on a five-point Likert scale (1 = *Strongly disagree*, 3 = *Neutral*, 5 = *Strongly agree*). Example items included autonomy for LA "I have a sense of freedom to make my own choices when utilizing learning analytics," competency for LA "I can completely achieve my teaching goals with learning analytics," and relatedness for LA "I experience positive feelings when I use learning analytics to help others (students, colleagues, etc.)." The measurement of basic psychological needs for LA is critical as it informs a faculty member's sense of autonomous motivation for LA, and the utilization of LA practices in their courses.

Faculty Motivation for Learning Analytics

Faculty member's motivation for LA utilized the continuum of motivation types in SDT adapted from Stupnisky et al.'s (2018; 2019a) studies of faculty motivation for teaching and research. Faculty were prompted to engage with a series of statements regarding their engagement with learning analytics and responded to 18 items measured on a five-point Likert scale (1 = *Strongly disagree*, 3 = *Neutral*, 5 = *Strongly agree*). Example items measured motivation/regulation types of the SDT continuum; intrinsic motivation “I find using learning analytics exciting,” identified regulation “Learning analytics allows me to attain teaching objectives that I consider important,” positive introjected regulation “Using learning analytics boosts my self-worth,” negative introjected regulation “I would feel bad not using learning analytics,” external regulation “My university encourages me to use learning analytics” and finally, amotivation “Honestly, I don’t know why I would use learning analytics.” Constructs of faculty motivation for LA are a critical area of research as this will be one of the first studies, along with Amida et al. (2022), to quantitatively measure items theorized under SDT for LA.

Power Analysis

Prior to data collection, a predicted sample for survey completion was proposed between 150-300 university faculty in the request for IRB approval. This proposed sample aligned with previous literature on SEM methodology where Kline (2011) suggested a sample of ~200 cases depending on model complexity; additionally, Kline (2023) suggested a (20:1) ratio of observations to model parameter. A-priori power calculation for the primary form of analysis in this study utilized Soper’s (2023) A-Priori Sample Size Calculator for Structural Equation Models. Anticipated effect size was indicated as 0.3 (i.e., Medium), with desired statistical power level at 0.8 and an alpha level of .05. In total, nine latent variables were included in the hypothesized model with 49 observed variables. Power calculation indicated a minimum sample size to detect effect as $N = 184$, with a minimum sample size of $N = 133$ for model structure, and a cumulative recommended minimum sample size based on the indicators as $N = 184$.

Data Analysis

The primary data source of the current study was survey data collected in the Qualtrics platform, which was downloaded and cleaned primarily through Microsoft Excel (Microsoft Corporation, 2023), and data analysis was performed in R-Studio (R Core Team, 2018). Analysis of the hypothesized model and research questions included four levels of analysis. First, to address the research questions (RQ1) and (RQ2), descriptive statistics were employed to provide numerical and graphical representation of the sample to organize, present, and analyze the data (Fisher & Marshall, 2008). Descriptive statistics explain faculty members' perceptions and utilization of LA in their courses, as well as perceptions of trust and control as it pertains to course data and their universities to address RQ1. Second, analysis of variance (ANOVA) was employed to address research question RQ2, in order to understand the potential mean differences among categorical variables to explain faculty motivation for LA, sense of institutional trust and control with course data, and faculty utilization of LA in their courses. Third, correlations were utilized to test the strength of linear relationships among trust, control, basic psychological needs, motivation, and utilization of LA (i.e., RQ3). Fourth, structural equation modeling (SEM) assessed regression paths among latent variables for faculty utilization of LA in their courses between control and trust constructs, basic psychological needs for LA, and motivation for LA in the previously presented hypothesized model. SEM was employed because it allows for the estimation of measurement error while analyzing multiple latent variables, additionally in estimating regression paths within multiple outcomes simultaneously in the proposed model (Byrne, 2013), to address RQ4.

Ethical Considerations

With respect to ethical considerations for this study, Bryman and Bell's (2007) ten principles of ethical considerations for dissertation work was consulted. Ethical considerations included IRB approval and informed consent from participants, where faculty were provided sufficient information and assurances taken by the primary investigator and co-PIs in the protection of data and the protection of privacy for research participants. Upon reviewing study information, participants were given the option of a skip-logic question to participate or not participate in the study. Additional protections were considered through anonymous reporting in the survey where only e-mail addresses were collected from those wanting to participate in the gift card drawing. Additionally, this study avoids misleading information, deception, or exaggeration about the aims and objectives of the dissertation and its results.

Summary

This quantitative study developed a series of four research questions and the employment of nine measures related to faculty member's institutional trust, course data control, motivation for and utilization of LA in their courses. Survey data collected via social media resulted in a total sample of 492 responses, where after data cleaning and filtering a final sample of 250 (50% of the total responses) was analyzed for discussion.

CHAPTER IV

RESULTS

Chapter IV of the current study outlines the results of analysis described in the methodology of the previous chapter in an attempt to address four research questions. Beginning with a summary of the reliability and validity of study measures and transitioning into descriptive statistics, ANOVA results, correlations, and the results of structural equation modeling which includes exploratory factor analysis, confirmatory factor analysis, and path analysis.

Reliability and Validity

Overall, study variables and measures were evaluated for normality and outliers, where the majority of measures displayed sufficiently normal distributions (i.e., skewness < 2.3; Kurtosis < 7.0; Byrne, 2016). Additionally study multi-item scales were tested for reliability with Cronbach's alpha ($\alpha > 0.70$; Warner, 2013; see Table 1). Two measures were identified as not meeting the cutoff for reliability, specifically the two basic psychological needs of autonomy ($\alpha = .62$) and competency ($\alpha = .61$).

Table 1

Descriptive Statistics and Reliabilities of Study Measures

Measure	# Items	*M*	*SD*	Range	Skew	Kurtosis	α
Faculty Utilization of LA	8	2.52	0.87	1-5	0.28	-0.22	.843
Faculty Control of Course Data	5	2.73	0.96	1-5	0.09	-0.41	.827
Faculty Trust and Course Data	6	3.09	0.78	1-5	-0.19	-0.28	.803
Basic Needs for LA							
Autonomy	4	3.16	0.75	1-5	-0.26	-0.23	.625
Competence	4	3.13	0.74	1-5	-0.44	0.02	.617
Relatedness	4	2.79	0.79	1-5	-0.11	-0.14	.755
Motivation for LA				1-5			
Intrinsic	3	2.69	0.87	1-5	0.00	-0.27	.836
Identified	3	2.89	0.93	1-5	-0.27	-0.54	.826
[1] Autonomous Motivation	6	2.79	0.84	1-5	-0.31	-0.33	.892
Negative introjected	3	2.20	0.89	1-5	0.48	-0.34	.804
Positive Introjected	3	2.36	0.87	1-5	0.35	-0.24	.769
External Regulation	3	2.15	0.86	1-5	0.49	-0.28	.700
[2] Controlled Motivation	9	2.24	0.70	1-5	0.28	0.05	.839
Amotivation	3	2.79	0.95	1-5	-0.08	-0.61	.807

Note. Autonomous motivation[1] is the combination of Intrinsic and Identified regulation types, and Controlled Motivation[2] is the combination of Positive Introjected, Negative Introjected, and External regulation types.

Descriptive Statistics

Overall, the participants (N = 250) consisted of primarily White (85.8%) female respondents (71.9%), with an average age of (M = 40.2, SD = 9.19), where the majority had completed doctoral degrees (80.8%; see Table 2). Regarding academic standing, there was a balanced representation of assistant, associate, and instructor ranked faculty members, with only (11.4%) having a full professorship status. Additionally, there was a balanced representation of Carnegie classification institutions, with research universities (i.e., very high and high research activity) combining for a total of (42.8%) of the sample, followed by masters colleges and universities (21.2%), doctoral/professional universities (18.8%), and baccalaureate colleges & universities (17.2%). With respect to teaching format, a large section of faculty members taught entirely in-person instruction on their respective campuses (45.3%), with entirely online instruction (i.e., synchronous and asynchronous) representing (17.3%) of the sample.

Table 2

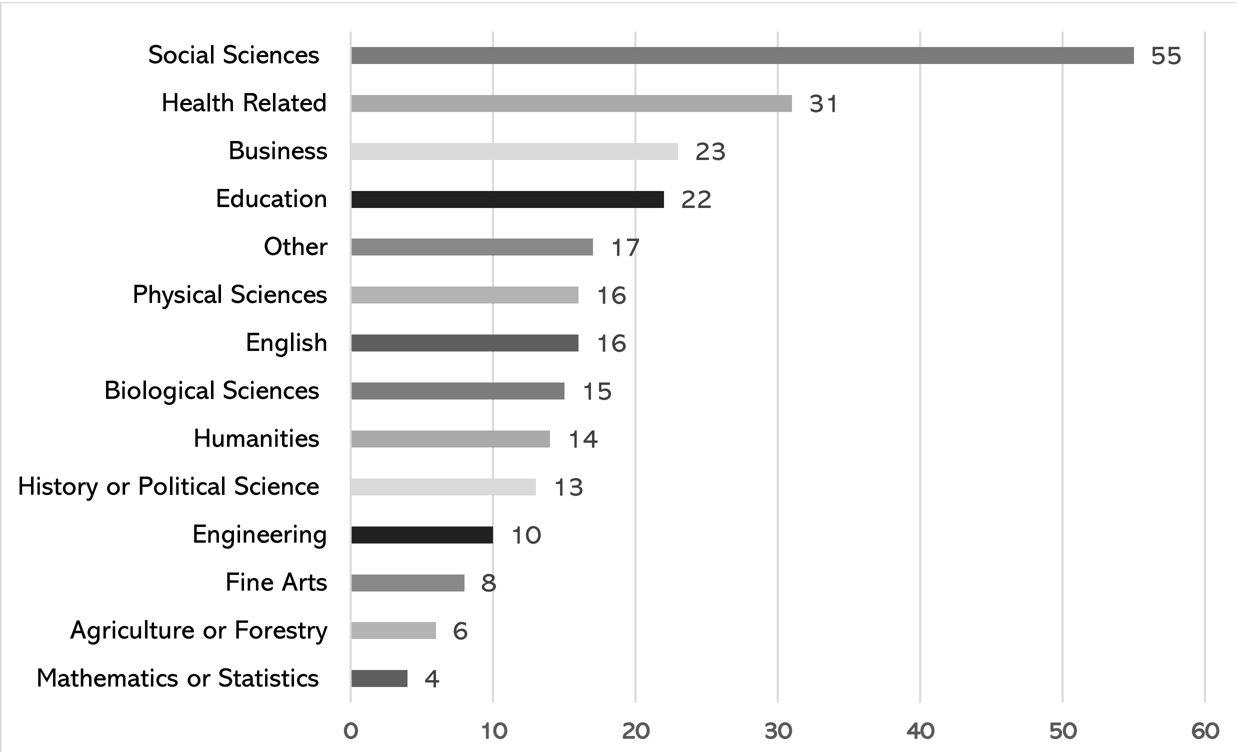
Participant Characteristics

		Count	Percent
Gender Identity	Woman	174	71.9
	Man	60	24.7
	Another gender identity	3	2.8
	I prefer not to respond	1	0.41
Racial Identity	White	207	85.8
	Asian	18	7.4
	Multi-Racial Identity	7	2.9
	Other	6	2.4
	Black or African American	3	1.2
Ethnicity	Not of Hispanic, Latinx, or Spanish Origin	205	82.3
	Yes, Mexican, Mexican American, Chicano	28	11.2
	Yes, Puerto Rican	9	3.6
	Yes, Another Hispanic	6	2.4
	Yes, Cuban	2	0.8
Highest Degree	Doctorate	198	80.8
	Masters	40	16.3
	Undergraduate	7	2.8
Academic Rank	Assistant Professor	91	37.1
	Associate Professor	73	29.8
	Instructor	30	12.2
	Full Professor	28	11.4
	Other (e.g., lecturer, adjunct, fellow)	17	6.9
	Research Scientist or Analyst	6	2.4
Tenure Status	Tenured	98	39.2
	On tenure track, but not tenured	81	32.4
	Not on tenure track	69	27.6
	Other (e.g., full-time, part-time, continued appointment)	2	0.8
Carnegie Classification	Doctoral University – Very High Research Activity	56	22.4
	Master's Colleges & Universities	53	21.2
	Doctoral University – High Research Activity	51	20.4
	Doctoral / Professional Universities	47	18.8
	Baccalaureate Colleges & Universities	43	17.2
Teaching Format	Entirely in-person instruction on campus	112	45.3
	A mix of in-person and online instruction	92	37.2
	Entirely online instruction (synchronous)	27	10.9
	Entirely online instruction (asynchronous)	16	6.4

Regarding academic fields, the majority of participating faculty were in the social sciences (22.0%), followed by health-related programs (12.4%), Business (9.2%), and Education (8.8%; see Figure 5).

Figure 5

Faculty Participants by Major Fields



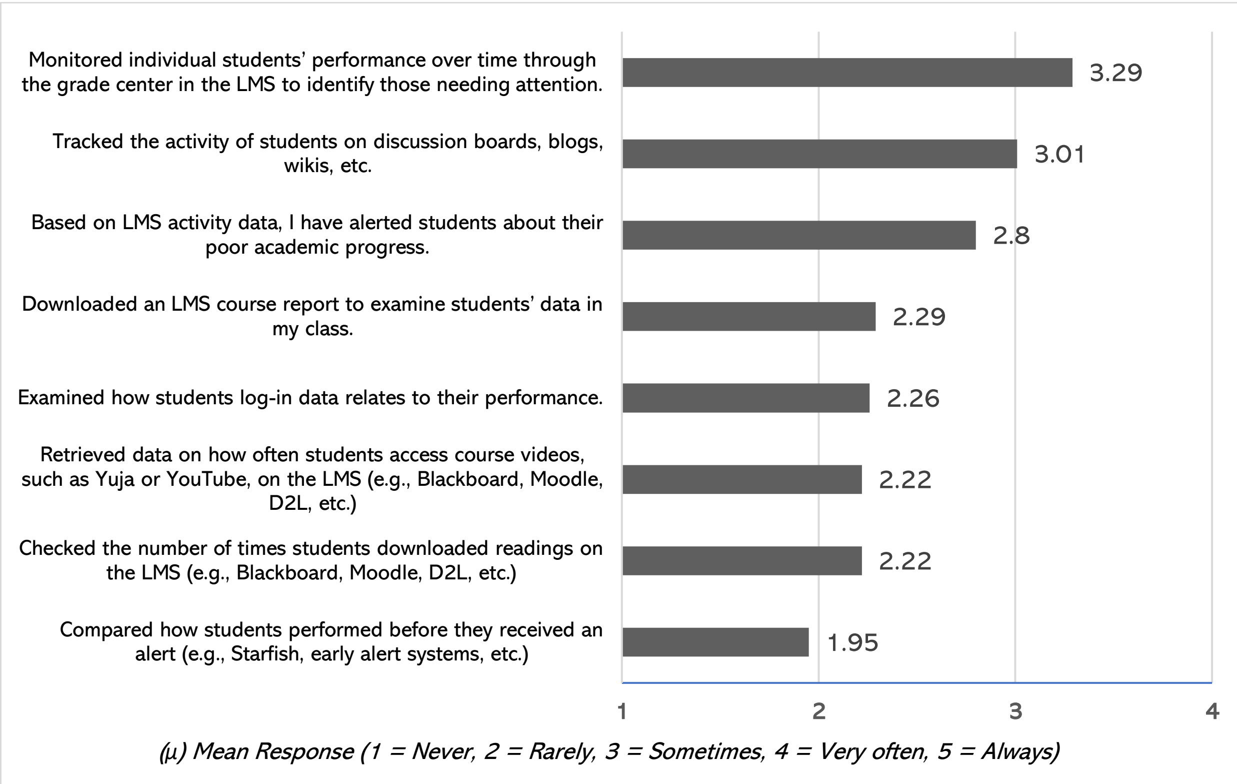
Note. Count(s) of participants by major academic fields.

RQ1. What are faculty members' perceptions and practices related to course data control, institutional trust with course data, and learning analytics utilization?

Results for RQ1 are centered around the measure of faculty utilization of learning analytics in their courses. In summary, faculty member's displayed the highest frequency of engagement with LA in their courses when monitoring student performance over time through the grade center of their LMS (M = 3.29, SD = 1.41), tracking student activity on discussion boards, blogs and wikis (M = 3.01, SD = 1.30), and alerting students about their poor academic progress based on activity observed in the LMS data (M = 2.8, SD = 1.42; see Figure 6). Among the lowest engagement of LA activities in faculty member's courses were the examination of student log-in data as it related to their performance (*M* = 2.26, *SD* = 1.07), and the comparison of student performance before receiving some form of early alert (*M* = 1.95, *SD* = 1.26).

Figure 6

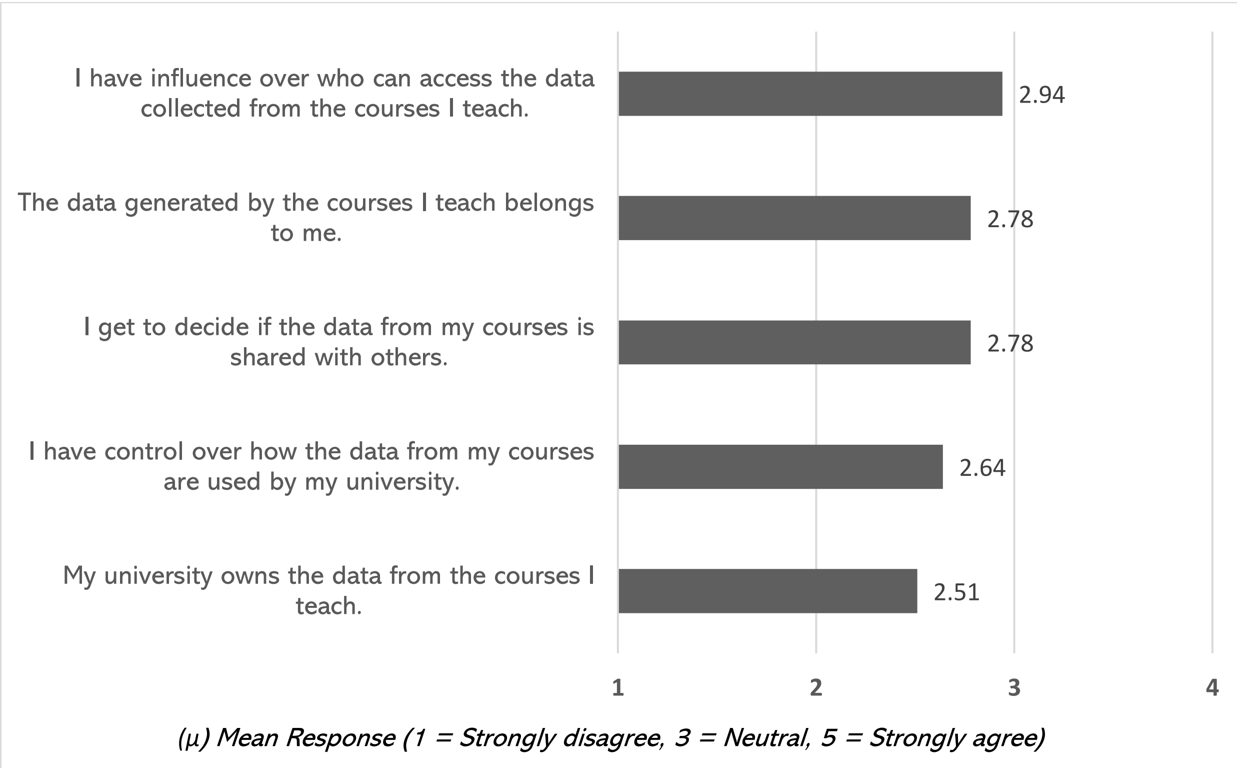
Faculty Utilization of Learning Analytics in their Courses



Faculty perceptions of control as it relates to their course data was another element of RQ1 (see Figure 7). Faculty indicated a nearly neutral sentiment regarding having influence over who can access the data collected from their courses (*M* = 2.94, *SD* = 1.27), followed by disagreement that data generated in their courses belongs to them (*M* = 2.78, *SD* = 1.35). The lowest average reported level of control came from a sentiment that the faculty members' universities own the data from the courses they teach (*M* = 2.51, *SD* = 1.19).

Figure 7

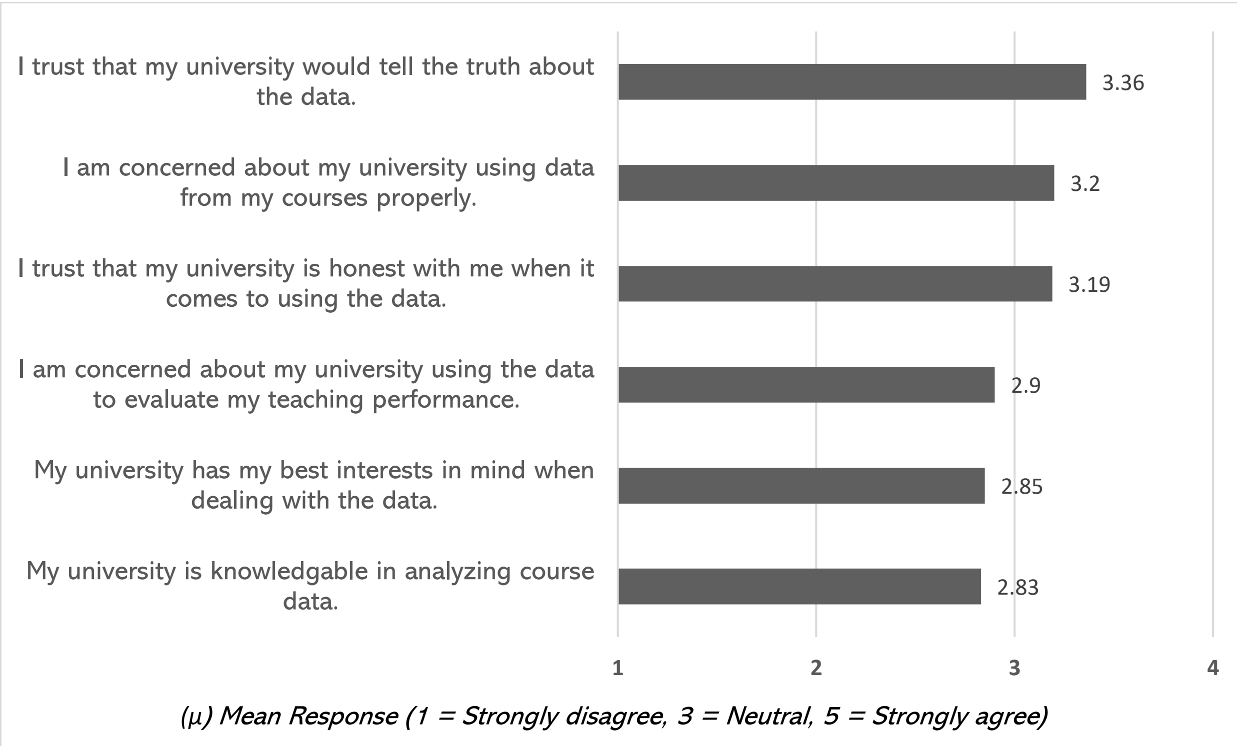
Faculty Control of Course Data



Lastly, faculty institutional trust as it relates to their course data was measured in fulfillment of RQ1 (see Figure 8). Overall, faculty reported a neutral sense of trust that their institution's would tell the truth in regard to LA data collected from their courses (M = 3.36, SD = 1.12), similarly with concern about the universities using the data properly (M = 3.2, SD = 1.11). The lowest recorded average for trust was in faculty members' believing that their universities were knowledgeable about analyzing the LA data from their courses (M = 2.83, SD = 0.99).

Figure 8

Faculty Institutional Trust and Course Data



RQ2. What differences exist among faculty with respect to autonomous motivation, controlled motivation, perceptions of performance evaluation, and the utilization of learning analytics in their courses?

Examining faculty characteristics in their comparisons on LA perceptions and utilization employed one-way ANOVAs to compare faculty perceptions and utilization of LA. Comparisons were made within LA utilization, autonomous motivation for LA, controlled motivation for LA, and performance evaluation, where performance evaluation was based on a single item "I am concerned about my university using the data to evaluate my teaching performance" on a 1-5 Likert scale (i.e., 1 = *Strongly disagree*, 3 = *Neutral*, 5 = *Strongly agree*). Faculty characteristics for comparison included primary teaching format, faculty member rank, tenure status, Carnegie classification, and academic fields.

Teaching Format

Comparisons of teaching format (e.g., On Campus, On Campus and Online, Asynchronous, and Synchronous) revealed a variety of significant results (see Table 3). First, faculty member's utilization of LA was statistically significantly different between those who taught asynchronously (M = 3.16, SD = 0.62) and other formats (see Figure 9). Additionally, faculty who taught primarily in asynchronous (M = 2.74, SD = 0.85) and synchronous (M = 2.78, SD = 0.73) online formats indicated higher levels of controlled motivation in comparison to online and a mixture of online and in person formats. With respect to performance evaluation, faculty who taught synchronously (M = 3.38, SD = 1.06) displayed higher concern regarding their course data being utilized for that purpose.

Table 3

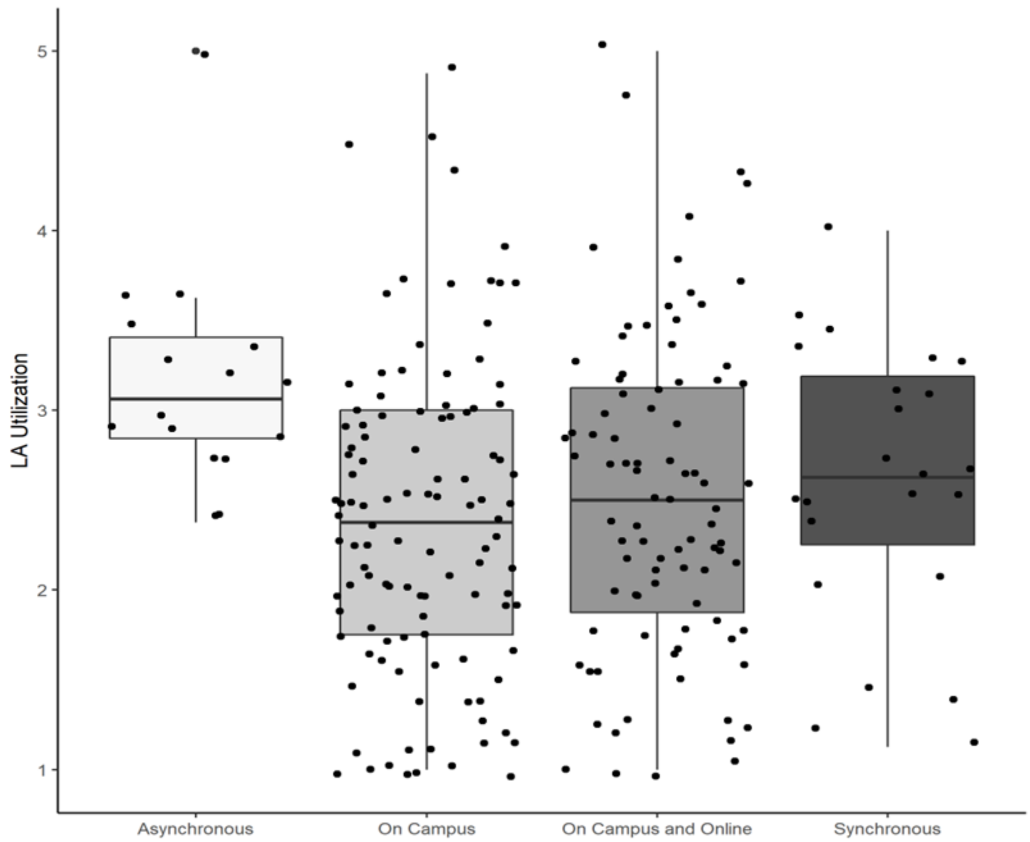
ANOVA of Teaching Format and LA Utilization, Autonomous Motivation, Controlled Motivation, and Performance Evaluation

			Teaching Format			
			On Campus	*On Campus and Online*	*Asynchronous*	*Synchronous*
Outcome	***F* (df1, df2)**	***p***	***M / SD***	***M / SD***	***M / SD***	***M / SD***
LA Utilization	4.16 (3,235)	<.01**	2.37 (0.62)^b	2.51 (0.89)^b	3.16 (0.62)^a	2.60 (0.77)^b
Autonomous Motivation for LA	0.73 (3,230)	>.05	2.80 (0.87)	2.73 (0.88)	3.05 (0.50)	2.7 (0.60)
Controlled Motivation for LA	12.06 (3,225)	<.001***	2.21 (0.68)^b	2.00 (0.55)^b	2.74 (0.85)^a	2.78 (0.73)^a
Performance Evaluation	4.50 (3,242)	<.01**	2.87 (1.16)^b	2.69 (1.19)^b	3.62 (1.20)^b	3.38 (1.06) ^{a}

Note. Superscript letters $^{(a)}$ and $^{(b)}$ denote group differences.

Figure 9

Boxplot of Teaching Format and Faculty Utilization of Learning Analytics



Faculty Rank

Comparisons of faculty rank (i.e., Full Professor, Assistant Professor, Associate Professor, and Instructor) also discovered a series of significant results in comparisons of LA and motivation variables (see Table 4). It is worth emphasizing the importance of selecting faculty rank as a categorical independent variable, where differences exist between full professors and instructors (e.g., adjuncts), full-time and part-time, and if a faculty member is tenured or in a tenure-track position. The primary difference between ranks are associated with contractual obligations of teaching, research, and service, and qualifications for different ranks are associated with institutional requirements. Specific to faculty rank, professional expectations are traditionally different, where instructors or adjunct faculty are focused more on teaching than research, and ultimately are more likely to be engaged with LA at the course level (Dringus, 2012). With that in mind, Associate Professors (*M* = 2.58, *SD* = 0.79) displayed significantly higher levels of autonomous motivation for LA in comparison to other ranks. Additionally, Instructors (*M* = 2.61, *SD* = 0.59) indicated significantly higher levels of controlled motivation in comparison to other ranks. While not statistically significant, Instructors also reported the highest levels of concern regarding course data control and performance evaluation (*M* = 3.20, *SD* = 0.96).

Table 4

ANOVA of Faculty Ranks and LA Utilization, Autonomous Motivation, Controlled Motivation, and Performance Evaluation

			Faculty Rank			
			Full Professor	*Assistant Professor*	*Associate Professor*	*Instructor*
Outcome	***F* (df1, df2)**	***p***	***M / SD***	***M / SD***	***M / SD***	***M / SD***
LA Utilization	1.15 (3,210)	>.05	2.59 (0.79)	2.42 (0.95)	2.52 (0.84)	2.76 (0.65)
Autonomous Motivation for LA	3.53 (3,206)	<.05*	2.61 (0.79)^{b}	2.95 (0.87)^{b}	2.58 (0.79)^{a}	2.97 (0.66)^{b}
Controlled Motivation for LA	5.61 (3,202)	<.01**	2.01 (0.60)^{b}	2.82 (0.66)^{b}	2.07 (0.66)^{b}	2.61 (0.59)^{a}
Performance Evaluation	1.37 (3,242)	>.05	2.57 (1.42)	2.9 (1.19)	2.8 (1.20)	3.20 (0.96)

Note. Superscript letters $^{(a)}$ and $^{(b)}$ denote group differences.

Tenure Status

Comparisons of faculty tenure status (i.e., Tenured, Tenure Track, and Non-Tenure Track) also revealed a series of significant results (see Table 5). First, non-tenure track faculty (*M* = 2.88, *SD* = 0.79) indicated higher levels of autonomous motivation for LA, and also indicated greater concern regarding course data being used for performance evaluation (*M* = 3.07, *SD* = 0.99) in comparison to faculty who were tenured or on tenure track. Tenure track (*M* = 2.39, *SD* = 0.70) and non-tenure track faculty (*M* = 2.40, *SD* = 0.73) also displayed higher degrees of controlled motivation for LA in comparison to those faculty who had already attained tenure status (see Figure 10).

Table 5

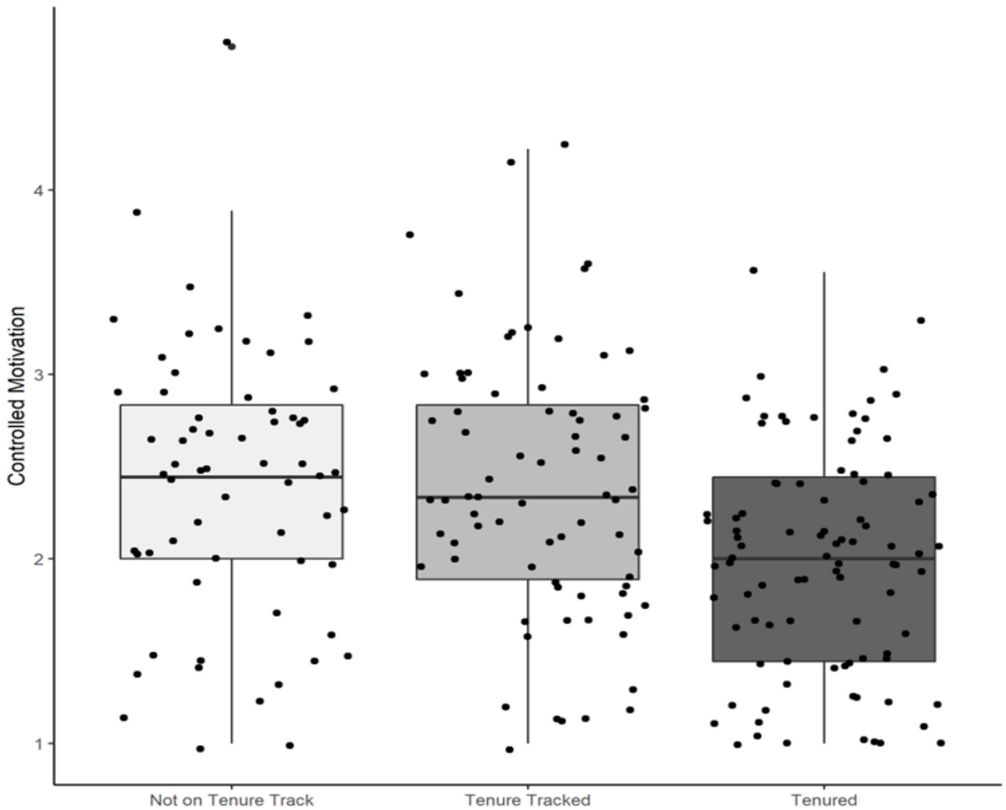
ANOVA of Faculty Tenure Status and LA Utilization, Autonomous Motivation, Controlled Motivation, and Performance Evaluation

			Tenure Status		
			Tenured	*Tenure Track*	*Non-Tenure Track*
Outcome	***F* (df1, df2)**	***p***	***M / SD***	***M / SD***	***M / SD***
LA Utilization	0.53 (2,237)	>.05	2.43 (0.83)	2.54 (0.83)	2.56 (0.97)
Autonomous Motivation for LA	4.54 (2,232)	<.05*	2.58 (0.83)[b]	2.94 (0.84)[b]	2.88 (0.79)[a]
Controlled Motivation for LA	10.34 (2,227)	<.0001***	1.98 (0.60)[b]	2.39 (0.70)[a]	2.40 (0.73)[a]
Performance Evaluation	4.48 (2,244)	<.05*	2.61 (1.19)[b]	3.06 (1.25)[b]	3.07 (0.99)[a]

Note. Superscript letters [(a)] and [(b)] denote group differences.

Figure 10

Boxplot of Controlled Motivation and Faculty Tenure Status



Carnegie Classification

Group comparisons among institutional Carnegie classifications (i.e., Doctoral R1, Doctoral R2, Doctoral Professional, Master's Colleges and Universities, and Bachelor's Colleges and Universities) additionally identified a statistically significant result (see Table 6). Specifically, Faculty who indicated working at Carnegie classified master's colleges or universities displayed the highest degree of statistically significant LA utilization (M = 2.85, SD = 0.77) in a comparison to the other institutional classifications. Additional results which were not statistically significant included higher degrees of autonomous motivation, and controlled motivation when comparing R1 and R2 doctoral institutions to professional, masters, and baccalaureate granting institutions. While not statistically significant, faculty from doctoral professional institutions indicated the highest degree of concern regarding course data being utilized for performance evaluation (*M* = 3.14, *SD* = 1.30).

Table 6

ANOVA of Institutional Carnegie Classifications and LA Utilization, Autonomous Motivation, Controlled Motivation, and Performance Evaluation

			Carnegie Classification				
			Doctoral R1	*Doctoral R2*	*Doctoral Professional*	*Master's C/U*	*Bachelor's C/U*
Outcome	***F* (df1, df2)**	***p***	***M / SD***	***M / SD***	***M / SD***	***M / SD***	***M / SD***
LA Utilization	3.82 (4,237)	<.01**	2.36 (0.87)[b]	2.25 (0.80)[b]	2.51 (0.96)[b]	2.85 (0.77)[a]	2.62 (0.84)[b]
Autonomous Motivation for LA	0.25 (4,232)	>.05	2.71 (0.85)	2.76 (0.89)	2.81 (0.87)	2.80 (0.78)	2.88 (0.80)
Controlled Motivation for LA	1.27 (4,227)	>.05	2.10 (0.60)	2.13 (0.70)	2.33 (0.76)	2.33 (0.73)	2.29 (0.70)
Performance Evaluation	1.63 (4,244)	>.05	2.66 (1.06)	2.88 (1.16)	3.14 (1.30)	3.09 (1.11)	2.73 (1.32)

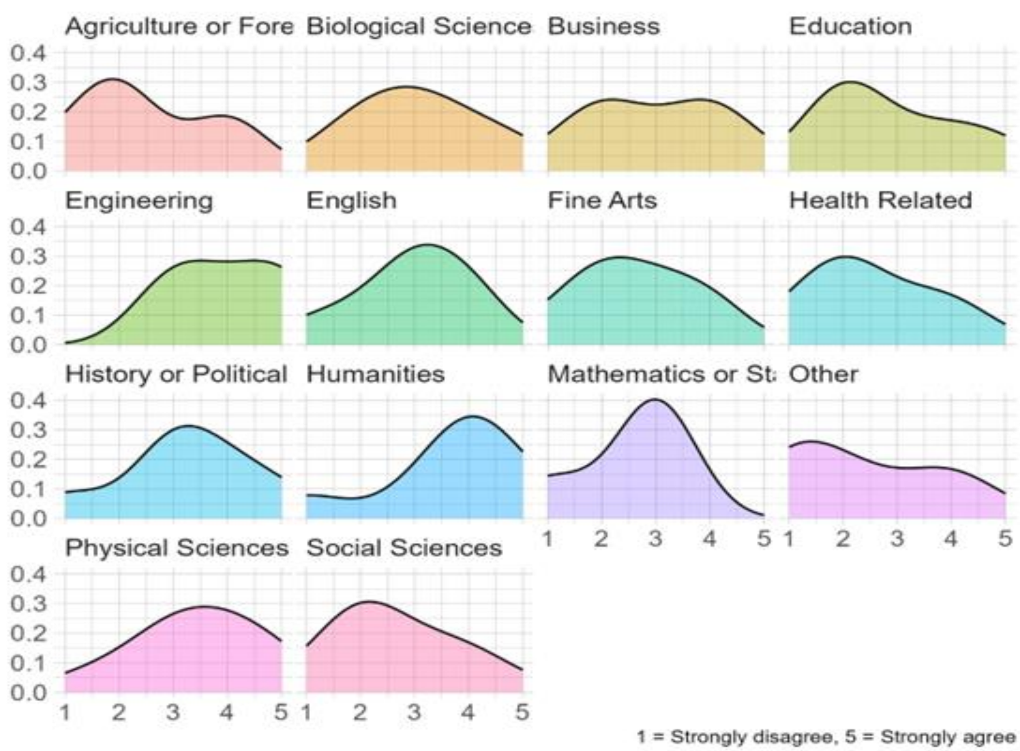
Note. Superscript letters (a) and (b) denote group differences.

Academic Fields

While statistically significant results in group comparisons of academic fields were limited, there was one statistically significant result. With respect to performance evaluation, academic fields were a statistically significant difference indicator $F(13,234) = 2.30$, $p < .01$, specifically between the highest reported level of concern among Engineering faculty (*M* = 4.00, *SD* = 0.94) in comparison to Health Related fields (*M* = 2.54, *SD* = 1.12) and "Other Academic fields" (*M* = 2.41, *SD* = 1.37), where other academic fields had the lowest indicated level of concern and consisted of majors including criminal justice, aviation, and communications (see Figure 11).

Figure 11

Faculty Members' Academic Fields and Concern Regarding Course Data for Performance Evaluation



Correlations

RQ3. What are the relationships among faculty course data control, institutional trust, basic psychological needs, motivation types, and learning analytics utilization?

Correlations included all measures of faculty course data control, institutional trust, basic psychological needs, motivation and regulation types, and the faculty member's utilization of LA in their respective courses. Additionally, faculty age was included as a continuous variable in the overall matrix (see Table 7). Throughout the matrix a series of statistically significant relationships were identified, where initially age had a negligible negative relationship with relatedness for LA (*r* = -.15) and controlled motivation (*r* = -.27). The faculty contract percentage dedicated to teaching revealed positive negligible correlations between competency for LA (*r* = .18) and LA utilization (*r* = .18), but a negative relationship with amotivation (*r* = -.14).

Faculty institutional trust with course data and sense of control with course data also had a series of statistically significant relationships. First, control of course data had a negligible positive correlation with institutional trust (*r* = .22), with comparable results for autonomy (*r* = .18), competency (*r* = .16), and relatedness for LA (*r* = .19). Institutional trust with course data also shared negligible positive correlations among autonomy (*r* = .19) and competency (*r* = .13), with a negative relationship in amotivation for LA (*r* = -.20).

Within basic psychological needs for LA, although reliabilities did not meet the appropriate criterium (α >.70) in autonomy and competency, it is worth mentioning their relationships among the other study measures. Basic psychological needs overall indicated moderate positive correlations among themselves, between autonomy and competency (*r* = .59), competency and relatedness (*r* = .68), and autonomy and relatedness (*r* = .66). Notably, autonomy and competency shared moderate positive correlations with autonomous motivation for LA, where relatedness had a high positive correlation for autonomous motivation (r = .70). Additionally, competency and relatedness shared low positive correlations with controlled motivation, with all three finding low to moderate negative correlations with amotivation for LA, with the strongest being competency (*r* = -.51).

Autonomous and controlled motivation for LA also shared a series of significant correlations with study measures. Controlled motivation for LA indicated a moderate positive relationship with autonomous motivation (r = .55), as well as a low negative relationship with amotivation (r = -.20), and a moderate positive correlation with LA utilization (r = .40). Autonomous motivation however shared a moderate negative relationship with amotivation for LA (r = -.60), and a moderate positive relationship with LA utilization (r = .48). Amotivation also displayed a low negative correlation with LA utilization (r = .42).

Table 7

Correlations of Age, Teaching Contract Percentage, and Study Measures with Confidence Intervals

Variable	1	2	3	4	5	6	7	8	9	10
1. Age	-									
2. Contract Teaching %	.06 [-.06, .19]									
3. Course Data Control	-.05 [-.17, .08]	-.11 [-.23, .02]								
4. Institutional Trust	-.02 [-.15, .11]	-.12 [-.24, .00]	.22** [.09, .33]							
5. Autonomy	-.06 [-.19, .06]	.01 [-.12, .13]	.18** [.06, .30]	.19** [.07, .31]						
6. Competence	-.01 [-.13, .12]	.18** [.05, .30]	.16* [.04, .28]	.13* [.00, .25]	.59** [.50, .66]					
7. Relatedness	-.15* [-.28, -.03]	.00 [-.12, .13]	.19** [.06, .31]	.12 [-.00, .25]	.66** [.58, .72]	.68** [.61, .75]				
8. Autonomous Mot	-.09 [-.21, .04]	.03 [-.09, .16]	.05 [-.07, .18]	.19** [.06, .31]	.68** [.60, .74]	.66** [.58, .72]	.70** [.63, .76]			
9. Controlled Mot	-.27** [-.39, -.15]	-.05 [-.18, .07]	.07 [-.06, .20]	.02 [-.11, .15]	.30** [.18, .41]	.39** [.27, .49]	.57** [.48, .65]	.55** [.45, .63]		
10. Amotivation	-.10 [-.22, .03]	-.14* [-.26, -.01]	.02 [-.11, .15]	-.20** [-.32, -.07]	-.38** [-.48, -.26]	-.51** [-.60, -.40]	-.41** [-.51, -.29]	-.60** [-.67, -.51]	-.20** [-.32, -.07]	
11. LA Utilization	.00 [-.13, .13]	.18** [.06, .30]	.01 [-.12, .13]	-.08 [-.20, .05]	.33** [.21, .44]	.52** [.42, .61]	.47** [.37, .56]	.48** [.38, .57]	.40** [.28, .50]	-.42** [-.52, -.31]

Note. Values in square brackets indicate the 95% confidence interval for each correlation. The confidence interval is a plausible range of population correlations that could have caused the sample correlation (Cumming, 2014). * Indicates $p < .05$. ** Indicates $p < .01$.

Structural Equation Modeling

RQ4. What factors predict basic psychological needs for LA, motivation for LA, and learning analytics utilization in faculty members' courses?

The hypothesized structural model for this study utilized previously established scales that were adapted to measure faculty sense of control in course data, institutional trust with course data, basic psychological needs for LA, motivation for LA, and finally the utilization of LA in faculty members' courses. Exploratory factor analysis (EFA) was still performed to validate consistent and reliable factors from the data. Prior to EFA model analysis, Bartlett's Test of Sphericity was employed to determine potential redundancy between variables that could be summarized with a limited number of factors, which resulted in sufficient correlation for factor analysis ($p < .001$). The Kaiser-Meyer Olkin Factor Adequacy KMO test was also performed and indicated that overall study variables had a mean sampling adequacy > .80, with exceptions being two variables in external motivation ($KMO = 0.69, 0.67$).

Parallel analysis observing the number of factors identified in the measures along with confirmatory factor analysis (CFA) identified variables which were removed from model inclusion. These included items *trustla_5* "I trust that my university is honest with me when it comes to using the data (i.e., learning analytics data from courses)", and *trustla23_6*, which was used as a standalone measure in ANOVAs, "I am concerned about my university using the data (i.e., learning analytics data from courses) to evaluate my teaching performance." Additional single items in autonomy and competency were removed as well. Additionally, two items were removed from the latent variable of faculty utilization of LA based-on modification indices strengths and descriptions from the initial scale which were not defined in the survey before item completion (e.g., Starfish, early alert systems, and course reports). While the latent variables of autonomy for LA and competence for LA did not display adequate reliability ($\alpha > .70$), they were included in the testing of the hypothesized model. However, based on model complexity a number of adjustments had to be made for analysis. Controlled motivation measured as a latent variable combining positive introjected, negative introjected, and external regulation types was instead presented as latent variables of negative introjected regulation and external regulation based on CFA results, which found that positive introjected motivation was not factor loading with negative introjected or external regulations. The hypothesized model also incorporated adjustments of modification indices in course data control variables for the purpose of identifying a potential relationship not captured by the latent variables of the model. This was also performed with measures between autonomy and competency with relatedness. Finally, based on model complexity, amotivation was excluded from initial analysis of the hypothesized model.

The hypothesized model used the established latent variables within the measurement model, where regression paths were specified from faculty control of course data and institutional trust with course data to basic psychological needs for LA. Latent variables for basic psychological needs for LA then displayed regression paths to their respective motivation and regulation types (autonomous motivation, negative introjected regulation, external regulation), with regression paths to the exogenous variable of faculty utilization of LA in their courses. The criteria used to assess model goodness of fit was comprised of chi-square (χ^2), comparative fit index (CFI > .95 indicating a well-fitting model, <.90 requiring respecification; Bentler, 1990; Hu & Bentler, 1999), standardized root mean square error (SRMR <.05 indicating well-fitting model, Byrne, 2016; <.05, Hu & Bentler, 1999), and root mean square error of approximation

(RMSEA <.08 indicating acceptable model fit, Browne & Cudeck, 1993; <.10 MaCullum et al., 1996).

Overall, the hypothesized model measurement did not display an adequate goodness-of-fit to the data $\chi^2(672) = 1316.578$, RMSEA = 0.066 (90% CI = .060 - .066), CFI = .850, TLI = .834 (see Figure 12). Covariates among course data control and trust were statistically significant ($\beta = .024$, $p < .05$), along with variability among basic psychological needs for LA, with no significant results between autonomous motivation, negative introjected regulation, and external regulation. In the hypothesized model, course data control significantly predicted faculty relatedness for LA ($\beta = .18$, $p < .05$) and autonomy for LA ($\beta = .20$, $p < .05$). Additionally, autonomous motivation for LA was a the strongest statistically significant predictor of LA utilization ($\beta = .54$, $p < .001$; $R^2 = 50\%$).

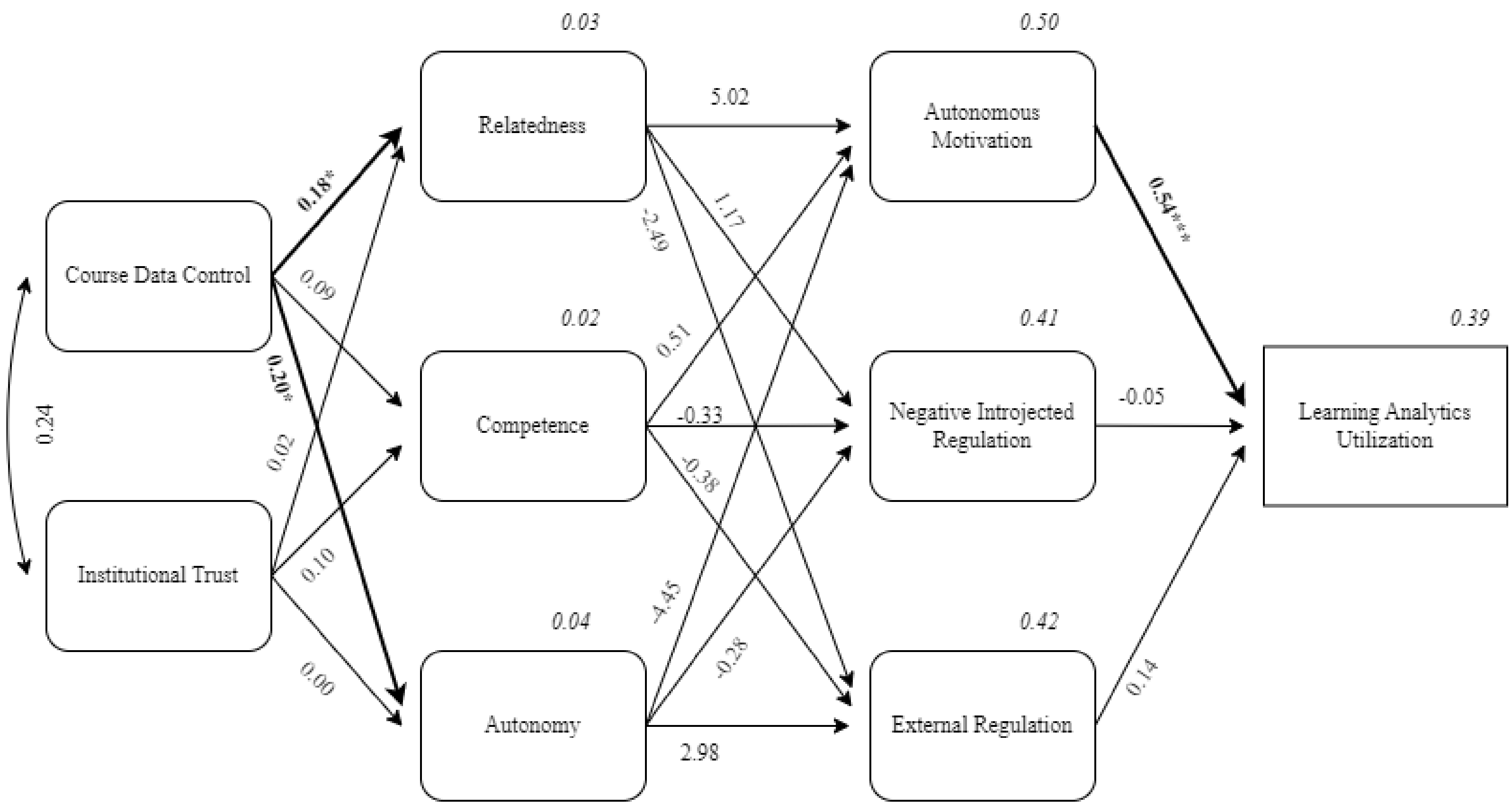
Based on the results of model measurement and structural paths of the hypothesized model, a modified model was developed post-hoc to further explore latent variable prediction of faculty members' use of LA in their courses. This decision was based primarily on poor-model fit displayed in the hypothesized model, and the inclusion of the endogenous measure of amotivation for LA in the post-hoc model with simplified model complexity. Overall, the modified post-hoc model measurement displayed adequate goodness-of-fit to the data $\chi^2(496) = 821.941$, RMSEA = 0.054 (90% CI = .047 - .060), CFI = .913, TLI = .901 (see Figure 13). Significant covariates were discovered between institutional trust for course data and control of course data ($\beta = .025$, $p < .01$), as well as between control of course data and relatedness for LA ($\beta = .08$, $p < .05$). Additional significant covariates were identified between autonomous motivation and external regulation for LA ($\beta = -.31$, $p < .05$), negative introjected regulation and external regulation (β = .48, $p < .01$), and between autonomous motivation and amotivation (β = -.51, $p < .001$).

In the modified model, there were a series of statistically significant predictors among latent variables and the exogenous outcome variable of LA utilization. Among the significant relationships, institutional trust for course data positively predicted autonomous motivation for LA (β = .10, $p < .01$), and negatively predicted amotivation for LA (β = -.16, $p < .05$). Additionally, faculty control of course data negatively predicted autonomous motivation for LA (β = -.12, $p < .05$), and positively predicted amotivation for LA (β = .28, $p < .01$). Relatedness, the only adequately reliable basic psychological need for LA (α = .75), significantly predicted autonomous motivation for LA (β = .63, $p < .05$), negative introjected regulation for LA (β = .47, $p < .05$), external regulation for LA (β = .13, $p < .05$), and negatively predicted amotivation for LA (β = -.54, $p < .001$).

Among latent variables of autonomous motivation for LA, negative introjected regulation for LA, and external regulation for LA, only amotivation was revealed to have a statistically significant negative predictive effect for faculty members' utilization of LA in their courses (see Figure 14). Specifically, amotivation, a lack of volition or value to engage with a task or behavior, became the single significant negative predictor of LA utilization in the modified model (β = -.41, $p < .01$; $R^2 = 37\%$). It is worth mentioning, that although autonomous motivation was not statistically significant, it would have been a positive predictor of faculty members' LA utilization in their courses (β = .28, $p = .09$; $R^2 = 72\%$).

Figure 12

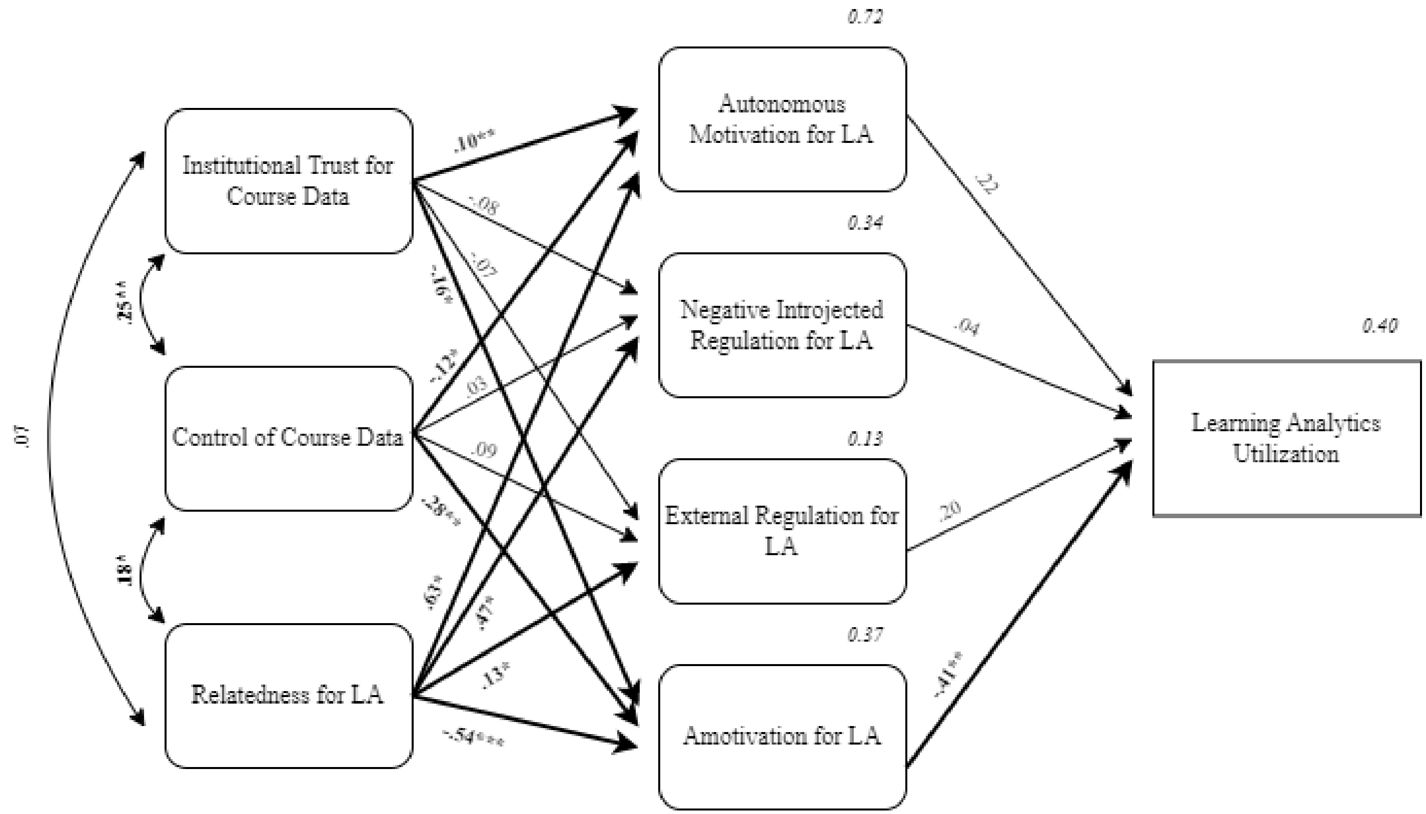
Hypothesized Structural Equation Model of Faculty Members Utilization of Learning Analytics in their Courses



Note. Standardized regression coefficients (β) appear on respective lines, with bolded paths and coefficients significant at * $p < .05$, ** $p < .01$. R-squared appears italicized above the right corner of endogenous variables. Analyzed sample was 250.

Figure 13

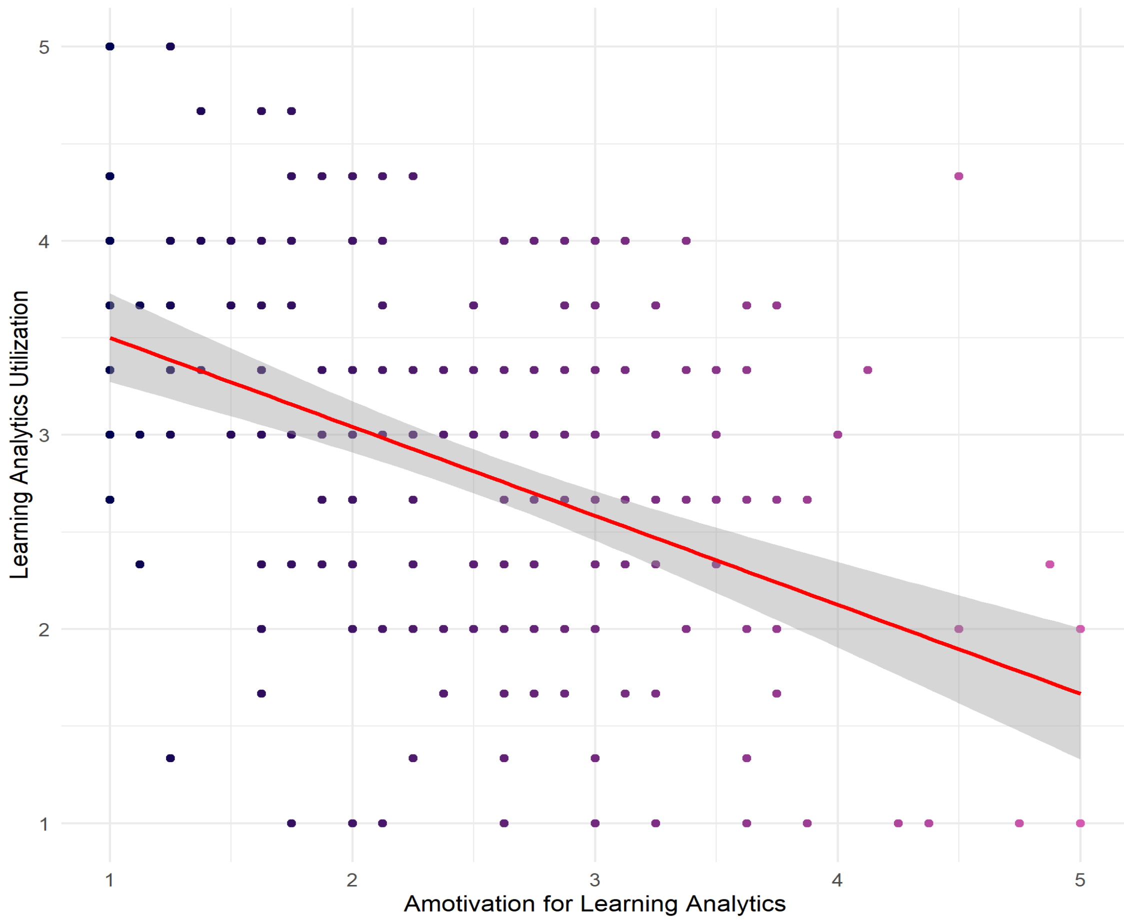
Modified Post-hoc Structural Equation Model of Faculty Members Utilization of Learning Analytics in their Courses



Note. Standardized regression coefficients (β) appear on respective lines, with bolded paths and coefficients significant at * $p < .05$, ** $p < .01$. *R*-squared appears italicized above the right corner of endogenous variables. Analyzed sample was 250.

Figure 14

Scatterplot of Amotivation for Learning Analytics and Learning Analytics Utilization



Limitations

There are a series of limitations to consider within this study. First, while a sweeping review of literature was conducted to understand faculty members' perceptions, utilization, and motivation for LA, there may still be previous studies which have looked at related topics but were elusive based on varied professional terminologies. Example's being the use of teacher or lecturer in other countries outside of the US in describing similar if not identical roles to faculty or professors. Second, data collection was conducted via social media platforms (i.e., Meta and

Twitter), where data cleaning and removal of duplicated responses was prioritized. While the social media outlet distributing the survey has an excess of 500,000 account follows, it would not be possible to measure survey engagement or response rates accurately based on lacking analytics data for post or link engagement.

With respect to the collected sample characteristics, the majority of respondents identified as white, female faculty members, which should be taken into consideration concerning result generalizability. Recent data from the National Center for Education Statistics (NCES) published data indicating that roughly 39% of full-time faculty identified as White males, with 35% identifying as White females, the totals of which shift depending on academic ranks in the fall of 2020 (National Center for Education Statistics, 2022). Within the context of this study, prior to data cleaning and filtering for the for the final sample of 250, the distribution of gender in survey respondents was roughly (69%) women, followed by (27%) men, with (3%) identifying another gender identity.

This distribution is worth investigating further and there are a few concepts to unpack within the context of the current study. First, previous literature suggests that the topic of a given survey could influence response rates (Groves et al., 2000). Moreover, in a paper by Smith (2008) which looked at the role of gender online survey completion among 278 university faculty, they suggest that faculty in varied areas of expertise are more likely than other faculty to respond to surveys. Smith also highlights the results of previous studies which suggest gender can influence online behavior. It is worth contextualizing that Smith's (2008) work does not appear to be published in a peer reviewed journal, however, but has a considerable number of citations potentially emphasizing a shortage of research concerning demographic variables in survey completion. However, in a recent study by Wu et al. (2022) that focused on online surveys, results suggest that gender could have an impact. Specifically, "when we examined the impact of gender on the online survey response rate, we found that male participants showed much lower response rates than female participants" (Wu et al., 2022, p. 9). Although this result was not statistically significant, the authors note that larger studies have demonstrated significant gender gaps in previous studies (Porter & Umbach, 2006), and moreover that differences between gender in online decision making and actions may play a role (Smith, 2008).

Additionally, faculty members self-identified the Carnegie classification of their current institutions which could not be verified, missing data could have also been the result of university and college faculty members who taught in countries where the Carnegie classification (i.e., outside of the United States of America) is not implemented, potentially deterring survey completion or estimation of where a faculty member's institution may be categorized.

Summary

This chapter summarized the results of the current quantitative study to reveal that faculty characteristics such as rank and tenure status identify significant differences in sense of institutional trust and data control, as well as motivation for LA in their courses. Structural equation modeling tested a hypothesized model which informed a post-hoc model for analysis and revealed that amotivation was a statistically significant negative predictor, and mediator of faculty utilization of LA in their courses. These results inform the final chapter of this dissertation in discussing the impact they have in an increasingly technology driven system of higher education.

CHAPTER V

DISCUSSION

The purpose of this study was to examine the role of institutional trust, course data control, and faculty motivation for LA in how those factors influence university faculty to use LA practices in their courses. Reviewing the literature, measures were developed and adapted to better understand faculty sense of institutional trust, course data control, and motivation types based on Deci & Ryans (1985) Self-Determination Theory. This led to the development and distribution of a survey administered to higher education faculty via social media platforms, resulting in a total sample of 250 faculty, made up of primarily females, who teach at Carnegie classified colleges and universities. Ultimately, four research questions were posed for primary analysis through ANOVAs, multiple correlation, and structural equation modeling. This chapter discusses the results of that analysis and connects them with previous research surrounding faculty perceptions and utilization of LA. These results provide a series of implications for critical consideration in higher education institutions going forward, as well as practical applications.

RQ1: *What are faculty members' perceptions and practices related to course data control, institutional trust with course data, and learning analytics utilization?*

Faculty Members' Control of Course Data

Beginning with faculty members' perceptions of course data control, overall, it appears that results were mixed in how faculty indicated a sense of control over the data collected in their courses. Across all items concerning faculty control of course data, averaged responses were classified in some element of disagreement which included faculty members' influence over who can access their course data, the data from their courses belonging to them, and sentiment that the data from their courses was owned by the university. These results are important as research surrounding faculty member's sense of control and ownership as it pertains to course data has largely been absent or centered upon on student perspectives (Hoel et al., 2017; Ifenthaler & Tracey, 2016). Additionally, these results inform a component of ongoing debate related to data ownership and legality in higher education (Drachsler & Greller, 2016; Tzimas & Demetriadis, 2021).

The general sentiment of disagreement among faculty regarding control or ownership over course data aligns first with a broader societal sense of lacking control or understanding of what data is being collected by them. In context, the majority of Americans indicate that they have little control over the data collected by them by companies or governmental agencies, along with little understanding as to what data is being collected, or how it is utilized (Pew Research Center, 2019). Further understanding of faculty sense of control or ownership over course data is also increasingly more important for LA engagement, as highlighted by Svinicki et al.'s (2016) study which found that faculty utilization of course data was influenced by faculty member's sense of autonomy or control in task engagement.

These results also call into question what influences a general sentiment of disagreement regarding control and ownership of course data, and connections that could be made with the results of Tsai et al.'s (2021) suggestion that trust in the context of course data control could indicate potential power diminution among faculty. Moreover, the context of which institutional stakeholders (i.e., heads of a college, directors, and deans) have control and access to the data has been influential in previous research centered upon faculty trust (Alzahrani et al., 2023), whereas this study focused on the faculty members' institution (i.e., university or college). Faculty members' control and ownership of course data aligns with an element of trust, and

Ferguson et al. (2019) notes that educators need to be able to trust the systems which control their data, and decisions made about learning processes within their courses.

Faculty Institutional Trust and Course Data

With respect to faculty sense of trust as it relates to their institutions and course data, faculty were asked to indicate their perceptions regarding LA data collected from their courses (e.g., tracked student activity data, grades, course content engagement, discussion board posts, etc.). Overall, faculty indicated a neutral to disagreeable sense regarding trust in their university as it pertains to the LA data collected in their courses. Among neutral average responses were a sentiment that a faculty members' university would tell the truth about data collected in their courses, their university using the data properly, and that their institutions were honest when using the data. General sense of disagreement arose regarding faculty members' university using the data to evaluate teaching performance, having the faculty members' best interests in mind when dealing with the data, and that the university being knowledgeable in analyzing course data.

First, these results are important as they are a continuation of research highlighting the importance of trust amongst the population of university faculty, which plays a critical role in student performance, faculty efficacy, and the overall health of an institution (Shoho & Smith, 2004). Trust is also a critical component between stakeholders and LA initiatives (Drachsler & Greller, 2016), but LA research in recent years has focused primarily on student trust as it pertains to LA (Jones et al., 2019; Mutimukwe, 2022). Additionally, university trust is an important component in educator decisions to use LA tools (Klein et al., 2019; Tsai et al., 2021) and engage with data driven decision making (Egetenmeier & Hommel, 2020).

The results of this study component act as a continuation of the work by Alzahrani et al. (2023) who suggest that trust should be considered in LA initiatives and practices, where "HEI's should prioritize the teaching staff's trust in LA through actions to better serve the goals of teaching staff as primary stakeholders in LA" (Alzahrani et al., 2023, p. 21). The role of trust in LA and in the technology driven trends of higher education institutions will only become a more prominent area of investigation over time. Especially within the context of artificial intelligence (A.I.), where early research suggests that a variety of factors can influence trust in A.I., such as human expertise vs. non-human expertise (Araujo et al., 2020).

Faculty Utilization of LA

With respect to faculty member's utilization of LA in their courses, there was a clear differentiation among different LA practices and the frequency to which faculty member's engage with them in their courses. Among those LA practices which had the highest levels of engagement were faculty monitoring student performance over time through their LMS grade center to identify those needing attention, tracking student activity in discussion boards, blogs, and wikis, and faculty members alerting students about their poor academic performance based on LMS activity data. These results align with Amida et al.'s (2022) study where faculty utilization of LA tools had the highest frequency of engagement with monitoring student performance through the grade center (86.3%), alerting students about poor academic performance based on course data (72.9%) and tracking student activity in discussion boards, blogs, or wikis (64.8%). It is worth noting that like the results of Amida et al. (2022), the present study found that faculty members indicated a low level of engagement with checking the number of times students had downloaded course readings or accessed course videos in the LMS.

However, the results of the current study found that faculty were not utilizing LA to compare how students performed before and after receiving a performance alert, whereas (52.0%) of the faculty in Amida et al.'s sample indicated some form of agreement that they were utilizing that tool/practice. The findings of the current study, in addition to the results of Amida et al.'s (2022) mixed methods study, act as a continuation of Svinicki et al.'s (2016) work to understand faculty utilization of course data for overall course improvement. One of the results with Svinicki et al.'s study highlighted that faculty specified a lack of resources to gather and utilize student data collected in their courses, which brings attention the results of the aforementioned studies where downloaded course reports have not been a priority for faculty members.

These results are important as it emphasizes a need to understand which LA practices or tools faculty find most valuable, practical, or effective in their courses, an area which needs further empirical support in how faculty perceive and use course data as part of their instructional practices (Hora et al., 2017). While general faculty perceptions of LA have been cautious and skeptical (Corrin et al., 2013; Dietz-Uhler & Hurn, 2013; Miles, 2015), these results should highlight what LA practices or tools faculty are currently engaged with in their courses, in addressing the ongoing challenge to understand educator and student benefits in utilizing LA (Arthars & Liu, 2020).

RQ2. *What differences exist among faculty with respect to autonomous motivation, controlled motivation, perceptions of performance evaluation, and the utilization of learning analytics in their courses?*

Teaching Format

First, with respect to the faculty characteristics, teaching format was found to be a significant indicator of LA utilization, controlled motivation for LA, and concern regarding performance evaluation based on course data. In summary, faculty members who taught in an asynchronous format displayed higher levels of LA utilization in their courses, and a greater sense of controlled motivation (i.e., external factors influencing their engagement with LA such as rewards, punishment, or job requirements). Similarly, faculty who taught primarily in a synchronous format also indicated higher levels of controlled motivation, and greater concern that course data would be used for performance evaluation.

These findings are a critical contribution by highlighting the importance of teaching format as an indicator of faculty engagement with LA practices, as found previously in Amida et al.'s (2022) study where course delivery format was a significant influence in faculty motivation to use LA tools in their courses. Additionally, these results are important in research concerning course delivery types (i.e., online, and blended) and technology integration through SDT (Ameloot & Schellens, 2018; Sergis et al., 2018). It is worth noting that overall, the largest differences among groups were typically between those faculty who only taught on campus in person, when compared to those who taught primarily in a synchronous or asynchronous format.

Faculty Rank

Faculty rank was also found to be a significant indicator of autonomous motivation for LA (i.e., using LA in a course out of enjoyment or personal importance), and controlled motivation for LA (i.e., using LA based on external pressures or rewards). Where Associate Professors indicated significantly lower levels of autonomous motivation for LA in comparison to other faculty ranks, and Instructors indicated a significantly higher degree of controlled motivation for LA in their courses. First, these results support Bollenback and Glassman's (2018) study which found that faculty rank, particularly in adjunct faculty (i.e., instructors in the present study), played a role in having contact with LA at the course level.

While the individual trust item (i.e., faculty concern of performance evaluation) was not significant, it is important to note that faculty rank was statistically significant in collegial trust, where adjunct faculty and Assistant Professors had higher levels of trust in their universities than full or tenured professors (Hoy & Tschannen-Moran, 1999). Additionally, the influence of faculty rank on motivation for LA contributes to previous research which has found faculty rank influential in research productivity (Stupnisky et al., 2022).

Tenure Status

Among faculty characteristics, tenure status had some of the most significant results. Surprisingly, tenure status was not influential in mean levels of LA utilization in faculty member's courses. However, non-tenure track faculty reported the highest levels of autonomous motivation for LA, and the greatest concern regarding course data being utilized for performance evaluation. Faculty members currently on tenure-track also reported significantly higher levels of controlled motivation for LA in comparison to those faculty who had already attained tenured status. This could indicate that those faculty members currently in the process of seeking tenure and promotion feel considerably more external pressure to utilize LA in their courses.

Focusing on performance evaluation, those faculty who were not tenure-track again reported the highest mean response of concern when responding to the question "I am concerned about my university using the data (i.e., LA data) to evaluate my teaching performance." This is an important result as it aligns with an overall sentiment of concern among faculty in LA data being used to assess faculty performance. While student evaluations of teaching have been a prevalent variable in performance evaluation, along with tenure and promotion (Abrami, 1990; Hornstein, 2017), they have drawn considerable criticism towards their validity and quality in assessing teaching performance (Boring & Ottoboni, 2016; Hornstein, 2017; Wines & Lau, 2016). This sentiment could create a potential opportunity for course data to be incorporated into performance evaluation and decisions on tenure and promotion, something that higher education institutions have indicated interest in previously (Arroway et al., 2016). This is something that cannot go overlooked in the current context of faculty tenure and promotion in higher education, especially within the context of the growth of A.I. platforms and their potential influence in performance evaluation, assessment, and accreditation efforts.

This emphasis on the role of faculty characteristics in performance evaluation cannot be overstated, as previously LA research has suggested that negative perceptions and concern towards LA could be in part based on its utilization to assess teaching performance and tenure decisions (Bollenback & Glassman, 2018; Dringus, 2012; Tsai et al., 2021). This could also be related to the concept of controlled motivation for LA, where a faculty member would only engage with LA practices based on external factors, such as contractual requirements, or the avoidance of punishment. In this context, faculty who were not on tenure track also indicated the highest levels of controlled motivation, where an argument can then be made that those faculty who have not yet attained tenured status would engage with LA for reasons which are much less self-determined.

Carnegie Classification

While results were limited, Carnegie classification was a statistically significant influence in faculty member's utilization of LA in their courses. Specifically, faculty members who taught at master's colleges and universities indicated the highest average level of LA utilization in comparison to other institutional types. Institution types have been found to be influential in faculty member's motivation for teaching (Stupnisky et al., 2018), however, neither autonomous nor controlled motivation were influenced in a statistically significant effect for LA based on institution type in this study. However, it appears there may be room for further investigation into the role institution types play in the adoption of LA initiatives and faculty utilization of LA in their courses.

Academic Field

Similar to the ANOVA results of Carnegie classifications, academic fields were limited in their influence on faculty motivation for LA or the utilization of LA in their courses. However, it is worth mentioning that faculty members in the field of engineering did have a statistically significant difference in levels of concern for course data being used in performance evaluation when compared to those in health or "other" related fields. While this result must take into consideration sample representation (e.g., sample including 10 faculty members in engineering), engineering had the highest overall level of concern among all academic fields in the sample and could inform future studies regarding LA perceptions and utilization among various academic fields. Moreover, in attempting to understand why there are potential differences in how perceptions differ among academics based on their prior knowledge or engagement with LA practices. This could also speak to additional research on how academic fields engage with LA differently, or even engage with LMS platforms and technology in general based on curriculum or course delivery methods in varied disciplines.

RQ3. *What are the relationships among faculty course data control, institutional trust, basic psychological needs, motivation types, and learning analytics utilization?*

Results from multiple correlations analysis revealed a series of significant relationships. First, faculty member's age was only significantly correlated with controlled motivation for LA, which suggests that there is a potential for the number of years a faculty member has been teaching in relation to their perceptions of LA as a controlling dynamic in the classroom. Additionally, the percentage of a faculty member's contract dedicated to teaching also displayed a small positive correlation with faculty member's sense of competency for LA, and utilization of LA in their courses. These results do shine some light on the potential for faculty member demographics and contract characteristics as potentially influential in their perceptions and adoption of LA in teaching, which has ultimately been an underdeveloped area of LA research.

Faculty sense of control with course data had a series of negligible positive relationships with institutional trust and course data, autonomy and relatedness, but ultimately did not share a relationship with any other measures in the study. Additionally, faculty members sense of institutional trust with course data had a series of negligible to small positive correlations with autonomy and competency, with a small negative correlation between amotivation, while these results leave more questions than answers, it does contribute to a growing area of research surrounding the role of trust and control or data ownership in how it influences faculty engagement with LA in their courses, areas which have just recently garnered more empirical exploration (Tsai et al., 2021; Alzahrani, 2023).

Basic psychological needs for LA were highly correlated amongst each other, especially moderately positive relationships between relatedness and competency and relatedness with autonomy. Based on a review of literature, it is unclear if basic psychological needs for LA has been measured previously, and the results are interesting in how much relatedness connected with faculty member's utilization of LA in their courses. This could be the result of faculty members utilizing LA in an attempt to support students by engaging with LA practices, or potentially through professional characteristics where colleagues feel a sense of belonging by engaging with LA. Specifically, if a faculty member is not present or in-person with their students, LA could provide an alternative avenue of relatedness by digital engagement, providing additional insight into online teaching formats. Basic psychological needs have also displayed moderate to strong significant correlations in previous work regarding teaching (Stupnisky et al., 2018), and research (Stupnisky et al., 2019b). Although the scales for autonomy and competency did not meet criteria for reliability ($\alpha > .70$), the results of the correlations do suggest that this is a potential area for further exploration in the role of basic psychological needs for LA utilization.

The constructs of autonomous motivation for LA (i.e., the combination of intrinsic and identified regulation) and controlled motivation (i.e., positive introjected regulation, negative introjected regulation, and external regulation) also had a significant series of relationships among study measures. Autonomous motivation for LA shared moderate significant correlations with basic psychological needs for LA, with the strongest being relatedness, followed by autonomy. Autonomous motivation was also moderately positively correlated with controlled motivation, and faculty member's utilization of LA. These results align with the findings of Amida et al.'s (2022) study, where intrinsic motivation (a component of autonomous motivation) was a significant small predictor of LA utilization among faculty, including the use of single and multi-click LA tools in their courses.

Amotivation for LA also resulted in a series of small to moderate negative correlations among study measures, the strongest of which were with autonomous motivation for LA, and competence for LA. Again, these results support those of Amida et al.'s (2022) study where amotivation was a significant moderate negative correlation for LA usage (r = -.43) and intrinsic motivation to use LA (r = -.55). Finally, faculty members' utilization of LA also displayed a series of positive low to moderate correlations with basic psychological needs for LA, along with autonomous and controlled motivation for LA. These findings are important in validating the results of Amida et al.'s (2022) study in utilizing SDT as an appropriate measure of understanding the relationship between a faculty members' motivation types and the utilization of LA in their courses.

RQ4. *What factors predict basic psychological needs for LA, motivation for LA, and learning analytics utilization in faculty members' courses?*

The primary purpose of this study was to examine the role of faculty motivation for LA in how it could predict LA utilization in their courses. The hypothesized model implemented measures of course data control and faculty member's sense of institutional trust with course data as predictors of basic psychological needs for LA, where basic psychological needs predicted autonomous motivation, controlled motivation, and amotivation for LA. Additionally autonomous motivation for LA, controlled motivation for LA, and amotivation for LA were hypothesized as potential predictors of the exogenous measure of LA utilization in faculty members' courses.

The hypothesized model however was ultimately adjusted by the results of tests of measure reliability, exploratory factor analysis, and confirmatory factor analysis which found that measures of autonomy and competency were not reliable, controlled motivation was instead broken down into measures of external and introjected regulation for LA, and model complexity resulted in the removal of amotivation as a predictor latent variable in the initial model test. The results of which found that the hypothesized model did not display adequate model fit. Path analysis results did find that faculty members' sense of control over course data was a significant predictor of both relatedness and autonomy for learning analytics, of which relatedness was the only basic psychological need with a reliable scale of measurement. This result suggests that while there is potential for basic psychological needs to act as predictors of motivation and regulation types for LA, more reliable measures would need to be validated and tested.

The results of the hypothesized model informed the development of a modified model to understand what factors influence faculty members' utilization of LA in their courses. The first step was to replace the basic psychological needs of autonomy and competency for LA with faculty sense of control over course data and institutional trust as it pertained to course data. The justification for this was due in part to a conceptual argument that a faculty members' sense of competency could be related to their sense of control over what happens with the data from their courses. Where if a faculty member feels a stronger sense of control and understanding of the data in their courses and how they influence the data, they would indicate a higher degree of competence to use LA. Although the result was negligible, there was a positive significant correlation between competence and course data control.

Additionally, institutional trust could in part fulfill the role of a faculty member's autonomy for LA practices in their courses, where if a faculty member does not trust their given institution with what happens with their course data, it would ultimately be influential in their sense of autonomy or independence to engage with LA practices. With the restructuring of basic psychological needs to now incorporate course data control and institutional trust along with relatedness for LA, amotivation for LA was also included in the model as a predictor of LA utilization based on the results of multiple correlations, where amotivation had a significant moderate relationship with LA utilization.

The resulting post-hoc modified model now displayed adequate fit and resulted in a series of latent variables as predictors in motivation for LA and LA utilization in faculty members' courses. The results found that institutional trust was a positive predictor of autonomous motivation for LA, and a negative predictor of amotivation for LA, whereas course data control was a negative predictor of autonomous motivation for LA and a positive predictor of amotivation for LA. In other words, the greater a faculty members sense of trust in their university in regard to their course data, the more autonomously motivated they would be for LA. Similarly, faculty member sense of relatedness for LA was a significant positive predictor of autonomous motivation, negative introjected regulation, and external regulation for LA. In other words, the more related faculty felt with their students and colleagues when engaged with LA practices, the more autonomously motivated they were for LA.

The key result of this post-hoc model analysis was that amotivation for LA was a highly statistically significant negative predictor of faculty member's utilization of LA in their courses behavior, became the single significant negative predictor of LA utilization in the modified model and a mediator that decreased the predictive power of autonomous motivation for. Amotivation in the context of this study would be a faculty members' lack of value, volition, uncertainty, and purpose in utilizing LA in their course.

Amotivation for Learning Analytics

The SEM results identified the predictive power of amotivation in LA utilization and is a key result for several reasons. First, a prevailing theme throughout the history of faculty technology adoption and LA as an individual field of research is faculty perceived skepticism or lack of value in the benefits of LA (Campbell, 2007; Corrin et al., 2013; Miles, 2015; Parry, 2012), which has been a historically underdeveloped area of research to understand how teaching related data is utilized in instructional practice (Hora et al., 2017). Additionally, the role of amotivation in education has centered upon academic tasks having little to no value to the stakeholder, meaning that there is little to no intrinsic or extrinsic motivation to participate or engage with an activity, therefore promoting task avoidance (Banerjee & Halder, 2021). This is concerning based on previous studies which found that intrinsic (i.e., autonomous) factors were important in technology adoption (Sugar et al., 2004), along with educator's perceived competence and usefulness of technology in predicting intrinsic motivation (Sørebø et al., 2009). The results of this study also align with the results of Amida et al.'s (2022) findings in that amotivation was a mediator of LA usage, and a negative predictor of multi-click LA tools, reinforcing the need to unpack the key components of amotivation in LA research surrounding faculty members.

With that in mind, the question should then be proposed as to what components of amotivation exist in their influence of faculty members using LA in their courses? Previous research has identified a lack of training or data competency as inhibitors of motivation or engagement with LA practices in the past (Amida et al., 2022; Dringus, 2012; Ifenthaler, 2017; Tsai & Gasevic, 2017), but the question then becomes how much of a role does that play in the amotivation of faculty to adopt LA in their courses? Moreover, if a faculty member is aware of the potential benefits of LA, or has engaged with information sharing and training with LA, does their degree of amotivation change?

Amotivation for Learning Analytics and Tenure

Traditionally, SDT posits that the support of basic psychological needs informs a healthy and self-determined degree of autonomous motivation for task engagement. Moreover, Ryan and Deci (2017) emphasize that SDT is a "meta-theory" that focuses on a critical distinction between autonomous versus controlled motivation. The result of this study, where amotivation was the primary predictive influence in faculty members using LA in their courses, is intriguing as it lies on the opposite end of the spectrum in relation to autonomous motivation (i.e., engaging with an activity with full willingness, value, or perceived importance of the task). Within the context of the landscape of higher education, this is a result that must drive further discussion.

This result is important to merge with two prevailing trends in the higher education landscape. The first being increased discussion, policy, and legislation related to faculty performance evaluation in tenure and promotion. In recent examples, faculty are grappling with state efforts to outright ban university tenure and promotion processes (Brown, 2023), and institutional policy changes such as those proposed at West Virginia University where "faculty members who receive unsatisfactory ratings in two areas in just one year must be recommended for "non-continuation" of employment" (Quinn, 2023).

While both of these examples are static and rapidly changing, they call into question the evaluation of faculty performance and where those data points come from. Specifically, if course data and LA utilization of institutions become a key indicator of faculty performance over the traditional student evaluation, a practice with considerable criticism (Boring & Ottoboni, 2016; Hornstein, 2017), what influence will this decision have on faculty promotion and tenure policies going forward? If faculty are increasingly amotivated to engage with LA in their courses, this could lead to an uninformed professoriate in both the data being generated in their courses, and moreover as to how that data could impact their careers in the future.

Amotivation for Learning Analytics and Artificial Intelligence

Another crucial element to consider in the present studies' finding of amotivation's negative predictive power for LA utilization among university faculty is the role of A.I. in how it will influence both their teaching and future careers. First, to provide a general definition, A.I. can be thought of as giving computers the ability to "perform near or human-like functions" (Chen et al., 2020, p. 75265). Recently, A.I. has garnered considerable media attention with the release of OpenAI's GPT-4 large language multimodal model that will have a sweeping impact across multiple industries. Examples of GPT-4's capabilities would include passing a simulation of the U.S. bar exam, writing poetry, and written essays on complex topics, capabilities that have spawned a rapid reaction among faculty with respect to assignment integrity in their courses (Heaven, 2023; OpenAI, 2023).

While A.I. has now gathered considerable attention in higher education, what may not be so obvious is that A.I. has already been integrated into numerous LMS platforms, either through independent platforms or integrated in already popular and widely used LMS platforms. Examples of this include the A.I. driven learning platform Obrizum, which emphasizes the platforms ability to automatically arrange learning content based on assessments, tailors learning to student progress, and analyzes learning progress in real-time, providing analytics based dashboards to drive data-driven decision making (Obrizum, 2023). The second example being the popular and widely used LMS Blackboard, which has developed a chatbot (Blackboard, 2023a), and has also recently promoted LA capabilities through the Rapid Online Analytical Reporting (ROAR) package (Blackboard, 2023b).

Linking all of this information with faculty members' amotivation for LA, it becomes very apparent that technological advances are already happening at a rapid pace in how data from courses is collected, and more so how it is turned into actionable data or informs data-driven decision making. Therefore, if faculty members do not currently have a strong understanding of the practices, benefits, or value of LA, it could impact their engagement and influence on the undercurrent of analytics already taking place in their courses. Moreover, if faculty are amotivated to engage with LA in their courses now, the trends and practices already in place could come as a surprise in decisions related to their performance evaluation and future careers.

This is one of the first studies to attempt introducing concepts of institutional trust and course data control as it influences motivation for this reason; where if faculty are not aware or feel limited in their autonomy as it relates to technology trends at their institutions it could limit their engagement with LA, and therefore their awareness of what is happening with the data being gathered from their courses. This rapid technological advancement and adoption in institutions of higher education is not a new phenomenon, and faculty need to be aware of what LA is, and why it could be a potential benefit or challenge in their teaching and careers.

Future Research

This quantitative study provides insight into faculty member's sense of control over course data, institutional trust as it relates to course data, basic psychological needs for LA, motivation for LA, and ultimately their utilization of LA in courses. Among the results were further clarification of understanding how faculty members currently engage in LA utilization in their courses, as well as their perceptions of institutional trust and control as it relates to course data. Future research based on the results of this study are two-fold. First, faculty concern for performance evaluation based on course data produced mixed results, where faculty displayed a level of disagreement or neutrality towards the concept, with some differences coming to the surface based on teaching format, tenure status, and academic fields. Historically, faculty have indicated varying degrees of concern and skepticism towards LA/course data being utilized for the purposes of performance evaluation, drawing comparisons with a “big brother” sentiment (Bollenback & Glassman, 2018; Dringus, 2013; Tsai et al., 2021). Given the rapid changes involving advanced statistical models and A.I. in LMS platforms used by higher education institutions, in combination with the recent changes surrounding faculty tenure and promotion, the results of this study inform future research on how perceptions of A.I. and the automation of decision making based on course data could influence faculty awareness or engagement with LA.

Moreover, institutions have indicated an interest in potentially using learning analytics in teaching performance evaluation (Arroway, 2016). Future research could incorporate measures to understand faculty member’s engagement with LA based on prior knowledge that such practices could be in play, or that their engagement with course data would be utilized for performance evaluation. With the growth of (A.I.) in learning management systems (Firat, 2023; Nadimpalli et al., 2023), this would be another area to incorporate as well into how performance is analyzed based on algorithmic versus human evaluation of teaching. Moreover, additional research should focus on faculty perceptions of A.I. processes and A.I. integrated platforms in a comparison of student evaluation versus the performance evaluation of the instructor.

The second line of future research based on the results of this study would be to further explore the role of amotivation in faculty member perceptions and engagement with LA practices in their courses. Moreover, breaking down the specific compartments of amotivation based on faculty member's perceived lack of value in utilizing LA, a lack of training to engage with LA, or even a baseline understanding of what LA is in relation to what capabilities already exist in their learning management systems. While previous studies have highlighted a lack of training as a critical component of LA utilization (Amida et al., 2022; Dringus, 2012; Ifenthaler, 2017; Tsai & Gasevic, 2017), it would be valuable to know what portion of amotivation was driven by a lack of training, and what portions are driven back due to a lack of perceived value or importance in the role of LA in positive student outcomes, an area which needs further empirical support (Viberg et al., 2018). In summary, it would be worth investigating further if faculty are amotivated for LA based on a perceived sense of value that course data analysis can provide, versus contractual obligations, or a hesitancy to engage with data that could be used to assess their performance as instructors.

Implications for Practice

There are several implications for practice that arise from the results of this study. First, in the literature that pre-dates the foundation of LA as an independent field, technology adoption among university faculty has historically been met with some degree of skepticism. Therefore, departments or programs in charge of implementing or creating LA initiatives should focus on two key areas. The first being transparency and information sharing as it relates to LMS platforms and data collection at a faculty members institution. Who owns the license for the LMS platform? What information is currently being gathered and where is it stored? Who has access to the data, and is the data currently being used on campus? These are questions that should be addressed prior to any technical training concerning the LA practices and tools that are available to faculty currently.

Moreover, the benefits of LA for a faculty member needs to be conveyed early on and supplemented with both practical and empirical support, an example being Smith et al.'s (2012) research that found student LMS logins, performance measurement in grades, and course material engagement predicted student overall course performance. These are all metrics that can monitored through LA practices in a faculty member's course and are often tools or features in an LMS platform. This conveyance of the benefits that LA can provide for faculty and students is an essential element in faculty buy in with respect to technology in their courses, where faculty who identified technology as having a positive effect on their teaching were more likely to adopt such practices (Mitra et al., 1999a;1999b; Spotts & Bownman (1995).

An additional practical implication based on the results of this study would be to address the numerous challenges faculty identify with LA in their courses when attempting to increase LA utilization. Faculty have previously identified that a lack of time and heavy workloads are constraining factors to engage with student data, especially those with contractual obligations primarily in teaching (Hora et al., 2017). Faculty have also suggested difficulty in engaging with LA tools based on a lack of data competency (i.e., the ability to access and interpret course data), and the quality of the data being collected. Therefore, departments and institutions who wish to promote LA practices or initiatives need to work with faculty to understand what practices or tools are being utilized, the competency of the faculty to engage with such tools/practices, and moreover the perceived value LA has. This can also include the collaboration of department heads or deans in how LA practices not only provide a series of potential benefits for students and improved teaching practices but can be compensated or supported through internal or external incentives.

With respect to implications for practice it is also worth investing in information sharing as to what role LA or course data, if any, in the tenure and promotion decision making process. If higher education institutions begin a transition away from traditional measures of performance evaluation to focus on faculty engagement with course data, or student performance based on course data, this information needs to be available.

Conclusion

This quantitative study is one of the first to attempt measuring faculty members' motivation to utilize LA in their courses through structural equation modeling, while also endeavoring to understand perceptions of course data control and institutional trust concerning course data. The results of this study highlight and support further evidence of SDT as an appropriate theoretical approach to understand faculty members' motivation to use LA in their courses, supporting the results of previous studies establishing the role of motivation in research (Hardré et al., 2011, Stupnisky et al., 2018), teaching (BrckaLorenz et al., 2012; Cook et al., 2009; Stupnisky et al., 2017), and LA (Amida et al., 2012; Marzouk et al., 2016; Schumacher & Ifenthaler, 2018). Additionally, while results highlight a need for supplementary study, faculty members sense of course data control and institutional trust pertaining to course data did play some role in how faculty engage with LA. Faculty characteristics such as teaching format, tenure status, and academic rank were also influential in how faculty experienced autonomous and controlled motivation for LA, how they perceived the role of course data in performance evaluation, and ultimately how they utilized LA in their courses.

Overall, among the results of this study was the critical finding through structural equation modeling that amotivation is a significant negative predictor of a faculty member's utilization of LA in their courses, potentially inhibiting faculty members' autonomous motivation where they would implement LA in their courses based on enjoyment or perceived importance in supporting positive student outcomes. The results of this study contribute to limited areas of research surrounding faculty perceptions and utilization of LA in their courses, and more so what factors a university should consider in developing or implementing LA programs that support faculty self-determination. Moreover, this is one of the first studies to not only introduce the factors of institutional trust and course data control in their influence of faculty motivation for LA but highlights the importance of amotivation as a negative predictor in faculty LA engagement. This result cannot be overemphasized in the context of rapid changes taking place across higher education as it relates to changes in performance evaluation and tenure, and the automation and algorithmic processes of A.I. in LMS platforms. These changes, which may appear to be futuristic on the surface are already becoming a more common practice in universities. Therefore, university faculty need to be aware of the potential benefits and challenges of LA, while also recognizing how LA could impact their courses, students, and future careers.

APPENDICES

APPENDIX A

IRB APPROVAL

UND.edu

Division of Research & Economic Development
Office of Research Compliance & Ethics

Principal Investigator: Robert Harrison Stupnisky
Protocol Title: Examining Faculty Perceptions of Innovations in Teaching and Research
Protocol Number: IRB0005450
Protocol Review Level: Exempt 2
Approval Date: 02/16/2023
Expiration Date: 02/15/2026

The application form and all included documentation for the above-referenced project have been reviewed and approved via the procedures of the University of North Dakota Institutional Review Board.

If you need to make changes to your research, you must submit an amendment to the IRB for review and approval. No changes to approved research may take place without prior IRB approval.

This project has been approved for 3 years, as permitted by UND IRB policies for exempt research. You have approval for this project through the above-listed expiration date. When this research is completed, please submit a termination request to the IRB.

Sincerely,

Michelle L. Bowles, M.P.A., CIP
she/her/hers
Director of Research Assurance & Ethics
Office of Research Compliance & Ethics
Division of Research & Economic Development
University of North Dakota
Technology Accelerator, Suite 2050
4201 James Ray Drive Stop 7134
Grand Forks, ND 58202-7134

APPENDIX B

STUDY RECRUITMENT INVITATION

|Eligibility

Are you a **higher education** faculty member?

|Study Overview

Our research examines the factors impacting faculty **motivation** for teaching and research.

You are invited to complete two anonymous online surveys, you can do one or both, and be entered into drawings for $50 Amazon gift cards (two drawings if you complete both surveys). After completing each survey, you will be given the opportunity to provide your email address in a separate form to be included in the drawings.

Each survey will take approximately **10-15 minutes.**

Impact of Social and Neurological Diversity

Survey Link:
https://und.qualtrics.com/jfe/form/SV_eVwLz1MgcEjXJJQ

Perceptions of Innovations in Teaching and Research

Survey Link:
https://und.qualtrics.com/jfe/form/SV_bf4eE4jFhaeSQYu

If you have questions or concerns please contact robert.stupnisky@und.edu.

Faculty Motivation Research Group (FMRG)
University of North Dakota (UND), USA

UND
UNIVERSITY OF NORTH DAKOTA

APPENDIX C

STUDY INFORMATION WITH INFORMED CONSENT

UNIVERSITY OF NORTH DAKOTA

Institutional Review Board

Study Information Sheet

Title of Project: Examining Faculty Perceptions of Innovations in Teaching and Research

Principal Investigator: Dr. Robert H. Stupnisky (707-777-0744, robert.stupnisky@und.edu)

Co-Investigator(s): Michael J. Herbert (michael.j.herbert@und.edu),

Oluwamakinde Omojiba (oluwamakinde.omojiba@und.edu)

Muhammad Salahuddin (muhammad.salahuddin@und.edu)

Purpose of the Study:

The purpose of this study is to examine faculty perceptions of current innovations in teaching and research. This includes measuring faculty motivation for learning analytics, mentorship, and self-reported proficiency with technology utilization when engaging with research activities. This quantitative study utilizes items from Self-Determination Theory (SDT) to measure faculty motivation for learning analytics and mentorship, as well as various items addressing technology use, self-reported teaching and research success, and faculty characteristics. There is a solid foundation of literature demonstrating the role of motivation and the impact it has on faculty success in teaching and research. Our study looks to expand this line of research to include perceptions of learning analytics, mentorship, and the utilization of various forms of technology in conducting research.

Procedures to be followed:

You will be asked to complete a survey containing a series of questions related to learning analytics, technology proficiency, and online mentorship. Once you have completed the survey you will have the opportunity to provide an e-mail address for a drawing of (1) of (10) $50 Amazon gift cards.

Risks:

There are minimal risks associated with privacy and confidentiality for participating in this study. To protect your privacy and confidentiality of information there are two primary protections in place. The first being the anonymity of faculty members who complete the survey. Second, e-mail correspondence for recruitment, survey completion, data exchange and the assignment of interview dates will only take place between the PI, Co-PI, and the individual participants. All other personal information outside of faculty requests to participate in the gift card drawing at the end of the survey will be anonymized. If you would like to talk to someone about your feelings regarding this study, you are encouraged to contact The University of North Dakota's Counseling Center at 701-777-2127 which provides counseling services to UND students at no charge.

Benefits:

The most important benefit includes faculty, who take part in the survey, will know they are contributing to our better understanding of faculty perceptions and motivation for innovations in teaching and research, along with the opportunity to participate in a drawing for gift cards upon completion of the survey.

Duration:

We expect that your taking part in this research will last approximately 20 minutes.

Statement of Confidentiality:

The survey does not ask for any information that would identify those who the responses belong to, therefore, your responses are recorded anonymously. If this research is published, no information that would identify you will be included since your name is in no way linked to your responses.

All survey responses that we receive will be treated confidentially and stored on a secure server. However, given that the surveys can be completed from any computer (e.g., personal, work, school), we are unable to guarantee the security of the computer on which you choose to enter your responses. As a participant in our study, we want you to be aware that certain "key logging" software programs exist that can be used to track or capture data that you enter and/or websites that you visit.

Right to Ask Questions:

The researchers conducting this study are Dr. Robert Stupnisky, Michael Herbert, Oluwamakinde Omojiba, and Muhammad Salahuddin. You may ask any questions you have now. If you later have questions, concerns, or complaints about the research please contact Dr. Robert Stupnisky at *[701-777-0744]* during the day.

If you have questions regarding your rights as a research subject, you may contact The University of North Dakota Institutional Review Board at (701) 777-4279 or UND.irb@UND.edu. You may contact the UND IRB with problems, complaints, or concerns about the research. Please contact the UND IRB if you cannot reach research staff, or you wish to talk with someone who is an informed individual who is independent of the research team. General information about being a research subject can be found on the Institutional Review Board website “Information for Research Participants” http://und.edu/research/resources/human-subjects/research-participants.html

Compensation:

You will not receive compensation for your participation. However, to encourage participants to complete the survey you will be offered an opportunity to provide your e-mail address for a drawing of (1) of (10) $50 Amazon gift cards.

Voluntary Participation:

You do not have to participate in this research. You can stop your participation at any time. You may refuse to participate or choose to discontinue participation at any time without losing any benefits to which you are otherwise entitled.

You do not have to answer any questions you do not want to answer.

You must be 18 years of age or older to participate in this research study.

Completion of the survey implies that you have read the information in this form and consent to participate in the research. *Please keep this form for your records or future reference.*

APPENDIX D

STUDY CODEBOOK

Examining Faculty Autonomous and Controlled Motivation for Learning Analytics

Michael J. Herbert

Dissertation Codebook

University of North Dakota

IRB PROTOCOL ID: IRB0005450

IRB APPROVAL DATE: February 16, 2023

DATA COLLECTION START DATE: March 9, 2023

DATA COLLECTION END DATE: March 30, 2023

Demographics

gender23	What is your gender identity? 1) Man 2) Woman 3) Another gender identity, please specify [text box – gender23_other] 4) I prefer not to respond
age23	What is your age? [Text Entry]
race23	What is your race? (select all that apply) 1) American Indian or Alaska Native 2) Asian (e.g., Chinese, Filipino, Asian Indian, Vietnamese, Korean, Japanese, Native Hawaiian, Samoan, Chamorro, etc.) 3) Black or African American 4) White 5) Other, please specify [text box, responses in race23_5_TEXT] 6) Multi-racial identity
ethn23	Is your ethnicity of Hispanic, Latinx, or Spanish origin? 1) No. I am not of Hispanic, Latinx, or Spanish origin 2) Yes, Mexican, Mexican American, Chicano 3) Yes, Puerto Rican 4) Yes, Cuban 5) Yes, another Hispanic, Latinx, or Spanish origin (e.g., Salvadoran, Dominican, Colombian, Guatemalan, Spaniard, Ecuadorian, etc.)

Faculty Details

highdegree23	What is your highest completed degree? 1) Undergraduate 2) Masters 3) Doctorate 4) Other, please specify [text box, responses in highdegree23_4_TEXT]
rank23	What is your current academic rank, title, or position? 1) Full Professor 2) Associate professor 3) Assistant professor 4) Instructor 5) Research scientist or analyst 6) If other please specify [Text box – rank23_6_text]
tenure23	What is your current tenure status? 1) Tenured 2) On tenure track, but not tenured

	3) Not on tenure track 4) If other please specify [Text box – tensuc20_4_text]
field23	In what major field is your current faculty appointment? 1) Agriculture or Forestry 2) Biological Sciences 3) Business 4) Education 5) Engineering 6) English 7) Health related 8) History or Political Science 9) Humanities 10) Fine Arts 11) Mathematics or Statistics 12) Physical Sciences 13) Social Sciences 14) Vocational 15) Other [text box]
Carnegie23	What is the current Carnegie Classification of your institution? 1) Doctoral University – Very High Research Activity 2) Doctoral University – High Research Activity 3) Doctoral/Professional University 4) Master's Colleges & Universities 5) Baccalaureate Colleges & Universities 6) Associates Colleges 7) If other please specify
format23	In what format do you teach? 1) Entirely in-person instruction on campus 2) Entirely online instruction where students attend class at specific times (synchronous) 3) Entirely online instruction where students always participate at times of their choosing (asynchronous) 4) A mix of in-person and online instruction
contract23	As stated in your contract for the current academic year, please specify your expenditure of time using percentages into the categories below: (The percentages should sum to 100%. If none for a category enter "0".) -Teaching (including advising/supervising students) - Research - Service - Other (e.g., administration)

Outlier Variable (FILTER)

OUTLIER23	Identifier variable for outliers (1) No data whatsoever on at least 1 item beyond the demographics/position description questions, or it is a duplicate response. (2) Missing data on the majority of items… too much for estimates/imputation (3) Missing data on a substantial number of variables but could still estimate/impute. (4) Full or very nearly full data on the majority of items

Current LA Utilization

Please indicate how often you have done the following to utilize learning analytics in your courses:

Scale: 1 = Never, 2 = Rarely, 3 = Sometimes, 4 = Very often, 5 = Always

lause23_1	Examined how students log-in data relates to their performance.
lause23_2	Checked the number of times students downloaded readings on the LMS (e.g., Blackboard, Moodle, D2L, etc.)
lause23_3	Tracked the activity of students on discussion boards, blogs, wikis, etc.
lause23_4	Retrieved data on how often students access course videos, such as Yuja or YouTube, on the LMS (e.g., Blackboard, Moodle, D2L, etc.)
lause23_5	Monitored individual students' performance over time through the grade center in the LMS to identify those needing attention.
lause23_6	Compared how students performed before they received an alert (e.g., Starfish, early alert systems, etc.)
lause23_7	Based on LMS activity data, I have alerted students about their poor academic progress.
lause23_8	Downloaded an LMS course report to examine students' data in my class.

Research items adapted from: Amida, A., Herbert, M. J., Omojiba, M., & Stupnisky, R. (2022). Testing and exploring the predictors of faculty motivation to use learning analytics to enhance teaching effectiveness. *Journal of Computing in Higher Education*, *34*(2), 545-576.

Faculty Control of Course Data

Please indicate the extent to which you agree with the following statements:

Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree

controlla23_1	I have influence over who can access the data collected from the courses I teach.
controlla23_2	I get to decide if the data from my courses is shared with others.

controlla23_3	My university owns the data from the courses I teach. **R**
controlla23_4	I have control over how the data from my courses are used by my university.
controlla23_5	The data generated by the courses I teach belongs to me.

Research items adapted from: Mutimukwe, C., Viberg, O., Oberg, L. M., & Cerratto-Pargman, T. (2022). Students' privacy concerns in learning analytics: Model development. *British Journal of Educational Technology*.

Faculty Trust and Course Data

In regard to learning analytics data from your courses (e.g., tracked student activity, grades, content engagement, discussion board posts):

Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree

trustla23_1	I trust that my university would tell the truth about the data.
trustla23_2	My university has my best interests in mind when dealing with the data.
trustla23_3	I am concerned about my university using data from my courses properly. **R**
trustla23_4	My university is knowledgeable in analyzing course data.
trustla23_5	I trust that my university is honest with me when it comes to using the data.
trustla23_6	I am concerned about my university using the data to evaluate my teaching performance. **R**

Research items adapted from: Mutimukwe, C., Viberg, O., Oberg, L. M., & Cerratto-Pargman, T. (2022). Students' privacy concerns in learning analytics: Model development. *British Journal of Educational Technology*.

Basic Psychological Needs for Learning Analytics

Regarding learning analytics, to what extent do you agree with the following?

Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree

aut23_la1	I have a sense of freedom to make my own choices when utilizing learning analytics.

com23_la1	I have confidence in my ability to improve my teaching by using learning analytics.
rel23_la1	I use learning analytics to feel closer to my students and colleagues.
com23_la2	I am capable of utilizing learning analytics.
rel23_la2	My use of learning analytics is supported by the people whom I care about (students, colleagues, etc.).
aut23_la2	My decision to use learning analytics reflects what I really want to do with my time.
aut23_la3	My choices to use learning analytics expresses who I am as a teacher.
com23_la3	I can competently achieve my teaching goals with learning analytics.
rel23_la3	I am close with people who are important to me when using learning analytics to improve my teaching (e.g., students, colleagues, etc.).
aut23_la4	I find it genuinely interesting to utilize learning analytics in my courses.
com23_la4	I can successfully complete complex teaching tasks with learning analytics, such as grading and monitoring student progress.
rel23_la4	I experience positive feelings when I use learning analytics to help others (students, colleagues, etc.).

Research items adapted from: Stupnisky, R. H., BrckaLorenz, A., & Nelson Laird, T. F (2019). Does faculty member's motivation for research predict their productivity? Testing a model of self-determination theory in a national USA sample. *International Journal of Educational Research, Special Edition on Faculty Motivation*, 98, 25-35.

Faculty Motivation for Learning Analytics

To what extent are the following reasons for why you engage with learning analytics?

Scale: 1 = Strongly disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly agree

intrin23_la1	I find using learning analytics exciting.
ident23_la1	Using learning analytics is important to me.

posintroj23_la1	Using learning analytics makes me feel proud.
negintroj23_la1	If I don't use learning analytics, I will feel bad.
extern23_la1	My university encourages me to use learning analytics.
amot23_la1	I don't know a good reason to use learning analytics.
intrin23_la2	It is enjoyable to use learning analytics for my courses.
ident23_la2	Learning analytics allows me to attain teaching objectives that I consider important.
posintroj23_la2	I want to prove to myself that I am capable of using learning analytics.
negintroj23_la2	I would feel guilty not teaching with learning analytics.
extern23_la2	My university pressures me to teach while utilizing learning analytics.
amot23_la2	Honestly, I don't know why I would use learning analytics.
intrin23_la3	I like using learning analytics.
ident23_la3	Teaching with learning analytics is important for the success of my students.
posintroj23_la3	Using learning analytics boosts my self-worth.
negintroj23_la3	I would feel bad not using learning analytics.
extern23_la3	I receive financial incentives from my college/university to utilize learning analytics.
amot23_la3	I wonder whether I should bother using learning analytics.

Research items adapted from: Stupnisky, R. H., BrckaLorenz, A., & Nelson Laird, T. F (2019). Does faculty member's motivation for research predict their productivity? Testing a model of self-determination theory in a national USA sample. *International Journal of Educational Research, Special Edition on Faculty Motivation*, 98, 25-35.

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