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The Acceptance of Learning Management Systems by Higher Education Faculty in an Educational Landscape Influenced by a Global Pandemic

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by

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Dedication

I dedicate this project first to God, who has always been my refuge and my fortress. I have always put my trust in the Almighty Creator, and because of that, I can rest in his shadow.

I further dedicate this to the love of my life and best friend, Josie, who has always encouraged me through thick and thin, helped me to see this through to the end, and endured the long nights spent online throughout the program. Best of luck in your research as well, and here is to the future Drs. Rektenwald.

To my children, Caleb and Summer, thank you for supporting your parents and their research. I hope you will be blessed beyond measure as you head upon your life's journeys. I hope that you know that you also can achieve anything you set your mind to.

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Thank you to my colleagues in the ACU Innovation Foundry, who endured conversations on technology acceptance for the last two years and helped to stir intellectual conversation as I explored this topic.

Abstract

This quantitative study investigated the perceptions of higher education faculty with respect to their behavioral intentions to use learning management systems and the perceived effect of COVID-19 on those intentions. An online survey was administered through private Facebook groups to faculty in higher education and listservs focused on technology in higher education. The sample size initially included 137 participants but participants were reduced to 121 due to incomplete responses on some surveys or not meeting the selection criteria for the research. The theoretical framework for this research was the intersection of the technology acceptance model and digital transformations. The data were analyzed using SPSS AMOS software to develop a structural equation model based on the technology acceptance model with the additional construct of the perceived effect of COVID-19 protocols. The results confirmed that the hypothesized model was a good fit and that COVID-19 had an effect on faculty members' perceived ease of use, perceived usefulness, and attitude toward use of learning management systems. The results also confirmed high behavioral intentions to use learning management systems in the future. Key findings of this research included a shift in the technology acceptance model's mediating variable that impacted the focus of professional development programs and the potential acceptance of learning management systems by higher education faculty in the foreseeable future.

Keywords: Technology acceptance model, learning management systems, COVID-19, Digital Transformations

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Chapter 1: Introduction

Digital innovations have impacted education throughout the decades, notably since the advent of the personal computer. Over time, educational leaders have been required to chart a fiscally and pedagogically sound path for implementing technological innovations. Technology's impact on educational policies and procedures increased dramatically in response to the global pandemic that began in 2019. Yancey (2020) referred to the disruption the pandemic caused to educational traditions and practices as "the 2020 winter of seeming despair, where sheltering-in-place and quarantine became the accepted standard" (p. 299). With a sudden shift to distance learning and social distancing, educators turned to technology solutions in the classroom to meet the needs of their students. Likewise, educational technology leaders turned to the technology acceptance model (TAM) as a guide to whether students and educators would adopt technology tools and used TAM's simple framework to shape the ideology of technology adoption.

Background

Since 1985, TAM has been an influential tool in predicting whether users will adopt technology systems (Correia et al., 2018; Oye et al., 2014). Davis et al. (1989) hypothesized that users would not adopt available computer systems solely because of significant performance gains. The variables that repeatedly demonstrated the highest correlation to actual technology adoption were users' perceptions about whether the technology was easy to use and valuable (Davis et al., 1989; Correia et al., 2018; Oye et al., 2014). Past research also demonstrated that TAM could only predict technology adoption success 30% of the time (Oye et al., 2014), although TAM has recently proven helpful as a model that facilitates the adoption of technology systems (Farooq et al., 2021).

Infrastructure and technical issues sometimes provide difficulties with the deployment of educational technology, and once those difficulties have been overcome, attitudes toward adopting the technology must also be overcome (Farooq et al., 2021). Without the adoption of the technology, deployment of that technology is fruitless.

The global COVID-19 outbreak impacted human lives worldwide (Cicha et al., 2021). With the rise of the COVID-19 global pandemic, many educational technology platforms were widely deployed (Narayandas et al., 2020). The organizational challenge of adapting education to distance learning and new technologies necessary to facilitate teaching from a distance resulted from adapting to the new reality of higher education for more than a year (Cicha et al., 2021).

According to Pomerantz (2019), the threshold for adoption of new technology before COVID-19 was "the technology must fit into instructors' existing practices, and the cost cannot be significantly higher than for the alternatives already in use" (p. 4). The changing teaching practices after the onset of COVID-19 required additional technical considerations. Two key questions arose: (a) Did the threshold for the adoption of learning management systems change? (b) Did the attitude toward learning management systems change? The ability of educational technology administrators to accurately and efficiently assess the acceptance of new technology before investing substantial resources of time and capital remains a critical problem. Since the development of the TAM, other models (e.g., TAM2; unified theory of acceptance and use of technology [UTAUT] model) extended TAM and increased its predictive efficiency by introducing new variables that complicate the initial TAM model (Oye et al., 2014).

According to the 2021 EDUCAUSE Horizon Report, one effect of the COVID-19 global pandemic was the increased adoption of blended or hybrid learning models, which led to increased adoption of educational technology practices and tools that support those models (Pelletier et al., 2021). This increased adoption of technology practices and tools in education may have also impacted higher education faculty members' general acceptance of educational technology. The question of interest is whether the COVID-19 global pandemic affected the acceptance of learning management systems (LMS) through the theoretical framework of the TAM model. Effects of a global pandemic reached higher education institutions worldwide, although regional differences in government and local higher education administration’s response to COVID-19 may affect perceptions of educational technology practices and tools such as LMS.

Statement of the Problem

The problem in context is whether a digital transformation (DX) occurred regarding the use of LMS amongst higher education faculty during the COVID-19 global pandemic. This potential transformation poses a problem because educational technology leaders have previously provided only niche support to higher education faculty on LMS for online learning. If a wider audience of higher education faculty now accepts LMS as a standard educational practice for engaging higher education students, new workshops and training for the development of online pedagogy will need to be implemented for highly diverse faculty who now view themselves as active participants in the use of LMS in higher education.

Purpose of the Study

The purpose of this non-experimental multiple regression study was to examine potential changes in the acceptance of LMS in higher education using the TAM and to provide suggestions that will inform educational technology leaders on the practice of the technology adoption of LMS. Data collection utilized online surveys in Qualtrics with global higher education faculty who recently adopted LMS. The Likert-style questions (other than questions for demographic data) generated quantitative data. The survey results were analyzed using SPSS to assess the behavioral intent to use LMS.

Research Questions

The central research question for this study asked: What is the impact of higher education institutions' response to COVID-19 on faculty acceptance of learning management systems? Research questions that framed the central question were:

RQ1: What is the effect of COVID-19 protocols on the perceived ease of use of learning management systems in higher education?

RQ2: What is the effect of COVID-19 protocols on the perceived usefulness of learning management systems in higher education?

RQ3: What are the perceptions of higher education faculty regarding the behavioral intent to use learning management systems during COVID-19?

RQ4: Has perceived acceptance of learning management systems changed for higher education faculty since COVID-19?

Definition of Key Terms

Acceptance. According to Schwarz et al. (2014), acceptance is a multi-dimensional psychological decision that receives the technology, comprehends the functionality and design of the technology, assesses the value and desirability of the technology, is willing to adapt routines to the technology, and finally submits to the intentionality of the technology.

Adoption. Bettiga and Lamberti (2017) defined technology adoption as a cognitive-affective process that leads to the formation of desire and then the consumption of technology.

Attitude toward technology usage (ATT). According to the technology acceptance model (Davis et al., 1989) and theory of planned behavior (Bamberg et al., 2003), ATT is a construct of the user's perceived usefulness and perceived ease of use (Fathema et al., 2015). According to Fathema et al. (2015), "attitude predicts his/her intention and intention shapes the actual behavior" (p. 212).

Barriers to adoption and use of technology. Lee and Coughlin (2015) described barriers as the factors or characteristics of one's perceptions of technology that impede the population's adoption of technology. perceptions about

Behavioral Intention (BI). According to Davis et al. (1989), behavioral intention is the measure of an individual's conscious decision to intend to follow through on a behavior in the future based on beliefs about consequences of the behavior.

COVID-19 global pandemic. In late 2019, an outbreak of a novel coronavirus was discovered and named SARS-CoV-2 "following a report of a cluster of cases of 'viral pneumonia' in Wuhan, the People's Republic of China" (World Health Organization, 2020). COVID-19 was identified as beyond a health crisis in 2020 as it had a broad societal impact by highlighting poverty and societal inequities on a global scale and was classified as a global pandemic (Asawapoom, 2021; Catalan et al., 2021).

Digital transformation (DX). According to Vial (2019), DX is "a process that aims to improve an entity by triggering significant changes to its properties through combinations of information, computing, communication, and connectivity technologies" (p. 121).

Educational technology. The field of educational technology is the theories and ethical practices in education that encompass research, instructional materials, and classroom environments (Guney, 2019).

Faculty. The group of individuals employed by higher education institutions with responsibilities related to direct educational instruction of their students, research in their academic specialty, and service to the university and its constituents comprise the institution's faculty (Hartman et al., 2007).

Global pandemic. A pandemic is an epidemic of an infectious disease that has spread across a large geographic region or international boundaries. According to the National Center for Immunization and Respiratory Diseases, Division of Viral Diseases (2020), "As COVID-19 began spreading in Wuhan, China, it became an epidemic. Because the disease then spread across several countries and affected a large number of people, it was classified as a pandemic" (para. 4).

Higher education. Clemmons et al. (2015) defined higher education as "Learning that occurs at a university, college, or institute beyond a high school level" (p. 179). Higher education is sometimes referred to as postsecondary or tertiary education (UNESCO Institute for Statistics, 2012).

Learning management system (LMS). A software platform that uses e-learning technologies to conduct online, synchronous, or asynchronous learning opportunities (Shurygin et al., 2021). The self-contained website permits faculty to organize engaging academic content to enrich learning opportunities (Fathema et al., 2015).

Online learning. Rodrigues et al. (2019) defined online learning as "an innovative web-based system based on digital technologies and other forms of educational materials whose primary goal is to provide students with a personalized, learner-centered, open, enjoyable and interactive learning environment supporting and enhancing the learning processes" (p. 95).

Perceived ease of use (PEU). Davis et al. (1989) defined PEU as “the degree to which the prospective user expects the target system to be free of effort” (p. 985).

Perceived usefulness (PU). Davis et al. (1989) defined PU as “the prospective user’s subjective probability that using a specific application system will increase his or her job performance within an organizational context” (p. 985).

Technology acceptance model (TAM). This theoretical framework adapts the theory of reasoned action to explain the acceptance of computer systems (Davis et al., 1989).

Theory of planned behavior (TPB). The TPB postulates that beliefs guide actions regarding the likely consequences, expectations of others, and factors that may inhibit or promote performance (Bamberg et al., 2003).

Theory of reasoned action (TRA). The TRA (Fishbein & Ajzen, 1980) is a more generalized predecessor to the TAM, which focused on social psychology and decision-making (as cited in Venkatesh et al., 2007). The TRA postulates that attitude influences behavior and the decision-making process developed in TAM (Rahim et al., 2022).

Unified theory of acceptance and use of technology (UTAUT). This expansion of TAM was developed by Venkatesh, Morris, Davis, and Davis (2003). According to Oye et al. (2014), UTAUT “condensed the 32 variables found in the existing eight models (TRA, TPB, TAM, MM, C-TPB-TAM, MPCU, IDT and SCT) into four main effect and four moderating factors” (p. 256).

Chapter 2: Literature Review

In this chapter, the background necessary to understand the research surrounding the TAM and the use of LMS in a time influenced by COVID-19 is presented as well as the theoretical framework of the TAM (Davis, 1989). Also explored is the development of TAM and other derivative models, the continued relevance of the TAM in research surrounding technology acceptance and adoption, the role of LMS in higher education, and the impact of the COVID-19 global pandemic on teaching with technology in higher education.

Literature Search Methods

The literature search was conducted through the online library resources and databases of Abilene Christian University. The Abilene Christian University library uses an EBSCO discovery service branded as OneSearch that allows researchers to identify relevant peer-reviewed scholarly literature. As a secondary resource, Google Scholar was used to create an alert for recently published articles using the search terms of COVID and technology acceptance model since 2020.

Theoretical Framework Discussion

TAM (Davis, 1989) was used as the theoretical framework to analyze whether reactions to the global COVID-19 pandemic impacted acceptance of LMS amongst higher education faculty. Davis (1989) developed TAM to explain and predict ATT and BI surrounding the potential use of information systems. Since TAM's development, TAM has become widely acknowledged as a model for technology acceptance in many disciplines and formats, especially in education (Chintalapati & Daruri, 2017; King & He, 2006; Sholikah & Sutirman, 2020).

In the context of this study, the adoption of LMS may have been mitigated by the DX in educational practices to a primarily online format (Ouajdouni et al., 2022). Before COVID-19, faculty predominantly used an LMS for teaching through voluntary choice (Catalan et al., 2021). The evaluation of the model comes with the reality that faculty may be forced to overlook the PEU, and the higher education faculty evaluating the LMS's PU because of the pandemic's forced DX.

Literature Review

The Impact of COVID-19 on Education

The COVID-19 global pandemic that began in 2020 impacted almost every person's daily life and interactions, either directly or indirectly (Camilleri & Camilleri, 2021; Ramasamy et al., 2021). These effects continue to affect higher education institutions even after the availability of vaccines (Al-Maroof et al., 2021). Governments implemented protective measures such as travel bans and a shift to online remote work and learning to slow viral infection spread (Strzelecki et al., 2020). This transition was done at the recommendation of local health agencies to prevent contagion by ensuring a socially distant environment (Işikgöz, 2021). Cicha et al. (2021) postulated that the primary question is "not how long the pandemic will last, but rather what impact it will have on the everyday lives of thousands of people around the world, and whether this impact will be permanent" (p. 1).

The impact of COVID-19 on global health and the economy was well-documented, and the education community was not immune. An estimated 87% of the world's school buildings closed by March 30, 2020, forcing 1.5 billion students and educators into unfamiliar arenas (Alfadda & Mahdi, 2021; Dhawan, 2020; Kim et al., 2021). The shockwaves of the COVID-19 pandemic were felt globally in higher education (Johnson et al., 2020). The Centers for Disease Control and the World Health Organization recommended the use of quarantines, social distancing, wearing masks, and sanitization of surfaces to flatten the curve regarding the spread of COVID-19 (Catalan et al., 2021). The first wave of COVID-19 forced most educational institutions to suddenly and unexpectantly interrupt face-to-face educational operations (Camilleri & Camilleri, 2021).

Stay-at-home or physical distancing orders came within mere days of the first infection within a country's borders (Johnson et al., 2020). These stay-at-home orders became known as lockdowns which imposed temporary closure of 'non-essential' operations (Bhatt & Shiva, 2020). During this transition, schools began to prepare their teachers with intensive technology and online education, while the students were often left to independently learn through their available and unequal technology (Alfadda & Mahdi, 2021). Students that found themselves incapable of using the online learning system led to dropouts, with faculty unable to provide adequate support (Ramasamy et al., 2021). According to Prasetyo et al. (2021), developing countries, like the Philippines, that found themselves without a sufficient infrastructure used mixtures "of modular learning, TV or radio broadcasts, and even through learning management systems" (p. 1).

Higher education leaders constructed contingency plans, became the voice for current research on the virus, and trained faculty and staff on how to work and teach remotely (Camilleri & Camilleri, 2021). The faculty training was necessary because the untrained found it challenging to continue instructional strategies and modify them to digital formats (Alturise, 2020). This shift to adapt traditional face-to-face teaching methods to a fully remote ecosystem was only designed as a temporary stopgap and was often called emergency remote teaching with the presumption that teaching would "return to the original format once the crisis ends" (Iglesias-Pradas et al., 2021, p. 2).

Almazova et al. (2020) spoke about higher education institutions' efforts to minimize the pandemic's negative impact as they tried to mitigate the interruption of teaching and learning. In the days and months following the beginning of the transition, gray literature in the form of blogs, editorials, and short reports emerged affirming the upheaval felt in higher education and providing support for faculty teaching remotely for the first time (Johnson et al., 2020). Kim et al. (2021) reported how “teaching staff had to scramble to set up and deliver remote lecturing and course materials through their institution’s LMS; at the same time, students were forced to switch to online systems for a new way of learning” (p. 1).

During the year following the onset of COVID-19, social distancing measures were put in place for those students and faculty on campus, while most were forced to design curricula for online delivery (Kim et al., 2021; Ramasamy et al., 2021). The transition to online classes was not a natural shift for many and often resulted in complications for faculty and students (Camilleri & Camilleri, 2021).

> The situation in higher education at the end of the first quarter of 2020 was both a surprise and a challenge for the University authorities, lecturers and students in the context of continuing the teaching process and the implementation of scientific research in such different conditions. (Ejdys & Kozlowska, 2021, p. 106)

According to Rubene et al. (2021), “the COVID-19 crisis overshadowed all of these reasons with an unprecedented and unavoidable need for long-term mass remote learning. This need could not be fully met by any other means than using technologies” (p. 182).

This global pandemic required schools to adopt online and distance learning principles even if their instructors were previously reluctant to accept this pedagogical approach (Catalan et al., 2021; Dhawan, 2020; Ejdys & Kozlowska, 2021). Leoste et al. (2021) found that while higher education faculty were familiar with their respective digital platforms, both faculty and students felt a lack of a sense of belonging during the COVID-19 pandemic because they “were not prepared enough for fully digital education” (p. 5). Alotaibi and Alajmi (2021) noted that the pandemic's critical nature covered any negative perceptions or difficulties and expedited the transition to online learning. Before COVID-19, almost one-third of all postsecondary students elected to study online, but the global pandemic made online learning compulsory for most students worldwide (Alfadda & Mahdi, 2021). The traditional model of in-person teaching was disrupted due to the higher contagion rate associated with COVID-19, which led to educators being forced to adopt online instructional methods (Farooq et al., 2021; Khamar Tazilah et al., 2021). Dindar et al. (2021) suggested that “the ongoing COVID-19 pandemic has triggered a new phase of technology use in educational settings” (p. 3). Ejdys and Kozlowska (2021) stated that while the pandemic has been disruptive to pedagogical practices, "remote learning can also provide continuity when face-to-face training is not available" (p. 106).

COVID-19 vaccinations were supposed to be a panacea for ending the effects of the pandemic. However, according to Al-Maroof et al. (2021), vaccine hesitancy by the population in general and specifically the education community has extended the effects into the foreseeable future. Qiao et al. (2022) reported that young adults might be experiencing low vaccination coverage due to vaccination hesitancy because of a lack of perceived severity among college-age adults.

Alhumaid (2021) noted that innovative teaching methods are more likely to be adopted during extraordinary circumstances, but the effect of COVID-19 has not been fully explored. Adopting online teaching and related technologies was not based on choice but out of necessity and fear, complicating whether TAM is strengthened in its predictive ability or needs to be adapted (Alhumaid, 2021). The abrupt transition to online learning highlighted difficulties caused by faculty members' lack of preparation and experience in online instructional design and LMS (Alotaibi & Alajmi, 2021). However, Catalan et al. (2021) asserted that this implementation of online learning in higher education would force online learning offerings at a higher rate postpandemic.

This pandemic is still not over, and it is unlikely that once the disease is eradicated, that culture will ultimately "return to pre-COVID life any time soon" (Farooq et al., 2021, p. 975). While policymakers have eased restrictions on social distancing, hygienic practices encouraged by schools amid peaks and troughs of COVID-19 cases kept faculty relying on remote learning technologies to teach (Camilleri & Camilleri, 2021). Sangeeta and Tandon (2020) argued for taking advantage of the opportunities presented by this medical crisis when the education space is utilizing online learning and increasing educator acceptance of the discipline rather than transitioning back to pre-COVID status. According to Bhatt and Shiva (2020), the lockdowns as a result of COVID-19 accelerated "the habit of digital connectivity for conducting the official work at home. The lockdown has force[d] people to use and adapt tools which are available over the internet" (p. 70).

The technologies developed and enhanced in the past made learning possible while school buildings were closed (Raza et al., 2021). Educators were exposed to new technology platforms that students and parents had to adapt to continue student education (Sangeeta & Tandon, 2020). By the end of 2020, it is estimated that at least 91% of the global learner population were exposed to the challenges of distance education, and because of this, educators were forced to adopt sustainable educational practices using technology solutions (Ejdys & Kozlowska, 2021; Sukendro et al., 2020). TAM helped guide many educational leaders in their distribution of technology solutions by demonstrating how technology could aid in their teaching performance and how easy the technology was to use (Farooq et al., 2021).

Research has demonstrated that other mitigating factors, such as fear, can impact technology acceptance and TAM (Alhumaid et al., 2021). Fear's mitigating factor can positively and negatively impact technology acceptance (Alhumaid, 2021; Alhumaid et al., 2021). Fear can sometimes be a positive perception, especially if that danger is real (Alhumaid, 2021). With these potential mitigating factors, TAM may face changes due to perceptions of technology usage. Sukendro et al. (2020) demonstrated the possibility of the pandemic being a facilitating condition affecting both PU and PEU. Balaman and Bas (2021) purport that the COVID-19 outbreak is one of the significant factors along with globalization and technological revolutions that have led to a shift towards online learning.

Raza et al. (2021) reported that because of its breadth of history in research that technology acceptance is seen as "a mature area in the role of information systems" (2021, p. 185). Since TAM is also an appropriate model for continuance intention, additional research is necessary to continue using online education post-COVID-19 (Khamar Tazilah et al., 2021). Farooq et al. (2021) touted the effectiveness of recent TAM research during the COVID-19 pandemic but that the effectiveness of online education could be aided through TAM and the increased acceptance of e-learning practices (Cheng, 2019).

The Development of TAM

Davis developed TAM based on Ajzen and Fishbein's (1980) theory of reasoned action (TRA) to model a user's acceptance of computer applications based on several factors (Alotaibi & Alajmi, 2021; Binyamin et al., 2019; Khamar Tazilah et al., 2021). TAM's uniqueness from TRA focuses on adopting new technologies and explains how behavior arises from intention, which stems from attitudes that follow perceptions (Gómez-Ramirez et al., 2019). In contrast, TRA focuses on the intention to act as a function of attitudes towards the action and societal norms (Fathema et al., 2015). While previous theories like TRA were general theories explaining human behavior, TAM focuses on using technology applications (Gómez-Ramirez et al., 2019).

TAM's original purpose was to assist information technology companies in developing applications that people would accept (Davis et al., 1989). Underutilization of technology already installed contributed to poor returns from the capital investment, and early researchers needed to understand the circumstances that would foster embracing the technology (Venkatesh & Davis, 2000). The removal of technical barriers with the development of computer information systems implied that developers needed to focus on what should be developed that users would accept, but this proved more nuanced than initially expected (Davis et al., 1989). Davis (1989) initially hypothesized that PU had a direct impact on BI while PEU only influenced PU though eventually, both were demonstrated to have an impact on BI (Khamar Tazilah et al., 2021).

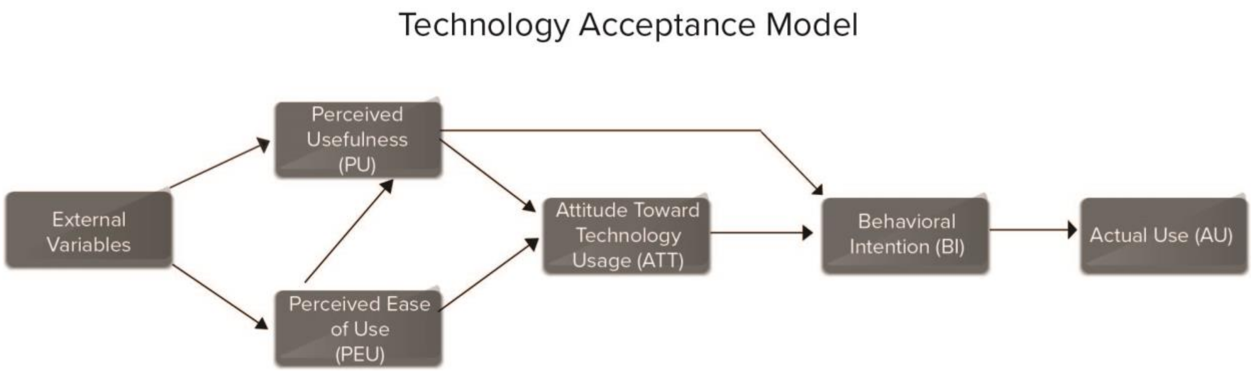
TAM Defined

TAM is a conceptual model that provides a theoretical background and support for the acceptance and adoption of technology (Davis et al., 1989). The theoretical model was built upon the relationship between five variables: (a) perceived ease of use (PEU), (b) perceived usefulness (PU), (c) attitude toward technology usage (ATT), (d) behavioral intention (BI) for use, and (e) actual use (AU; Akman & Turhan, 2017). The model develops causal relationships between PEU, PU, ATT, and BI (Gómez-Ramirez et al., 2019). According to Işikgöz (2021), the predictive model demonstrates that BI is affected by PU and PEU, which “respectively show the path of intention regarding the actual use of technologies” (p. 17). Figure 1 demonstrates how

TAM develops a relationship in which the potential adopter's ATT and expectations influence the opportunity of acceptance and thus the adoption of the innovation (Correia et al., 2018).

Figure 1

Technology Acceptance Model



Note: Adapted with permission from "User acceptance of information technology: System characteristics, user perceptions and behavioral impacts," by F. D. Davis, 1993, *International Journal of Man-Machine Studies*, *38*, p. 476 (https://doi.org/10.1006/imms.1993.1022).

TAM is helpful because of its simplicity and cost-effectiveness, in which the model flows from only two variables, making the model easily understood and simple to apply (Balaman & Bas, 2021; Kim et al., 2021; King & He, 2006). Those variables are how easy the technology is perceived to be to use (PEU) and how useful the technology (PU) will be to the user (Sholikah & Sutirman, 2020). According to King and He (2006), these TAM measures have been highly reliable and valuable in various contexts. Venkatesh et al. (2007) noted the robust number of studies that continue to utilize the model primarily "due to the parsimony of TAM, the robustness of its scales, and the strong generalizability of the model" (p. 268). Because of TAM's robust nature, influence on the field of information science, and breadth of examination, including being used as a comparison for analytical techniques, Venkatesh et al. (2007) stated that it is approaching law-like status.

Perceived Ease of Use (PEU)

The construct of PEU is an interpretation by the user that quantifies the user's belief that using the technology application will require no effort (Sholikah & Sutirman, 2020). When a user believes that technology will be of little to no effort, there is the potential to influence acceptance of the technology because easier-to-use technologies have a lower entry point, leading to the perception of being both useful and beneficial (Khamar Tazilah et al., 2021). In internet-based applications such as online learning environments and e-learning systems, PEU is a predictor of PU (Badri et al., 2016; Cheng, 2019; Liu et al., 2003).

The PEU is closely tied to a user's self-efficacy with technology (Venkatesh & Davis, 1996). A user's technology self-efficacy is rooted in their general sense of abilities surrounding information and computer technologies, which generates an anchor for their perceptions of new or unfamiliar systems (Venkatesh & Davis, 1996). Users who require little cognitive effort to learn the technology will perceive it as easy to use and are more likely to use the new technology (Balaman & Bas, 2021).

Whether positive or negative, firm beliefs concerning computer self-efficacy significantly impact any computer system's PEU (Venkatesh & Davis, 1996). There is also a high positive correlation between PEU and PU, as users who find the functions of a new technology easy to use also consider the new technology useful (Bhatt & Shiva, 2020).

Perceived Usefulness

The construct of PU is the interpretation of the user's belief that the technology will help maximize their performance of the intended task (Ruangvanich & Piriyasurawong, 2019; Sholikah & Sutirman, 2020). A strong belief in PU can influence and overcome barriers to technology acceptance as the user will be willing to achieve the valuable qualities (Khamar

Tazliah et al., 2021). PU is utilitarian as it quantifies effectiveness in performance and why this technology is essential to enhancing job performance (Gómez-Ramirez et al., 2019; Sánchez-Mena et al., 2017).

PU and PEU help shape the user's BI towards the use of a technology, which then shapes the AU of the technology (Fathema et al., 2015). Users with a robust BI are also highly likely to have AU (Fathema et al., 2015). TAM helps explain BIs and the AU of technology directly and indirectly (Sholikah & Sutirman, 2020).

PU has been found to substantially influence BI more than PEU (Davis, 1989; Dumpit & Fernandez, 2017). A positive relationship between PEU and PU has also been noted (Dumpit & Fernandez, 2017; Venkatesh & Davis, 2000). This positive relationship implies that as users find the system less complicated, they will also consider them to be more useful (Dumpit & Fernandez, 2017)

TAM is helpful in the context of technology adoption, such as deciding whether a learning management system will be accepted and used by faculty members (Fathema et al., 2015). The faculty members will first decide whether they find the technology easy to use and valuable. This perception develops a positive or negative ATT. This ATT develops BI and finally influences the AU of the learning management system. According to Ramasamy et al. (2021), PU is a significant component of BI and has been well documented in its strong connection to e-learning acceptance, especially by learners.

The Criticisms of TAM

While TAM is appreciated for its simplicity, it has also been criticized for the lack of detailed guidance because it only provides a general framework (Albarghouthi et al., 2020). Over the years, numerous modifications have been made to TAM based on emerging technologies

(Fearnley & Amora, 2020). The modifications result from researchers' beliefs that "only two indicators is not sufficient to predict user behavior toward a variety of technologies across different contexts" (Kim et al., 2021, p. 1). The plethora of modifications and the lack of clarity have led to a lack of unanimous consensus in the research community on a single best model (Fearnley & Amora, 2020).

The development of additional derivative models to understand technology acceptance has been because of the criticism of the simplicity of TAM (Moodley et al., 2020). Marangunić and Granić (2015), for example, in their literature from the inception of the framework to their current day, found major modification categories for TAM: external predictors of PU and PEU, factors for increasing predictive validity, contextual factors, and usage measures. These models hope to increase the effectiveness of TAM by increasing the explanation of variance in the model through increased factors.

Researchers have also questioned the predictive power of the TAM, with some studies placing the successful prediction of technology adoption as low as 30% – 40% (Oye et al., 2014, p. 255). Others cite that although TAM is more predictive than other models, such as the TPB, those psychological models provide more helpful information for developing the support of student learning (Cheng, 2019). King and He (2006) also noted that not all technology acceptance relationships would work, as demonstrated by the wide variation between users and systems.

Finally, TAM does not consider any barriers that might inhibit the actual adoption of the technology (Oye et al., 2014). TAM assumes that once a user intends to use the technology, they will likely actually use the technology and not encounter any infrastructure or technical barriers.

Oye et al. (2014) tell of barriers "such as limited ability, time constraints, environmental or organizational limits, or unconscious habits which will limit the freedom to act" (p. 252).

The Derivatives of TAM

Research that attempts to extend TAM has primarily been with variables that could influence PEU and PU (Albarghouthi et al., 2020). Dumpit and Fernandez (2017) noted the number of studies involving TAM that “have continually identified new constructs that play major roles in influencing the core variables (PU and PEU) of TAM” (p. 4). The additional variables are an attempt to add robustness to the model by improving the predictive value of the tool (Oye et al., 2014). Ejdys and Kozlowska (2021) noted that the model is influenced by external features and capabilities of the system being measured, which will lead to additional variables that provide increased predictive accuracy. Additional variables that have been researched and have demonstrated effectiveness across multiple technological innovations are system quality, computer self-efficacy, facilitating conditions, access to technology, and planning time (Fearnley & Amora, 2020). Usually, the models are extended based on what researchers believe are mitigating variables within their circumstances or related to their technology (King & He, 2006; Šumak et al., 2011).

Additional models have been derived that are significant to be named a new model. Davis et al. (1989) derived many models, such as TAM1, TAM2, and TAM3 (Ejdys & Kozlowska, 2021). The additional TAM models utilized the determinants of "perceived usefulness, job relevance, output quality, result demonstrability, ease of use, subjective norm, image, BI, computer self-efficacy, perception of external control, computer anxiety, computer playfulness, perceived enjoyment, use behavior" (Ejdys & Kozlowska, 2021, p. 108).

In 2000, Venkatesh and Davis proposed an extension of their model after finding that PU was often the primary determinant of BI (Marangunić & Granić, 2015; Venkatesh & Davis, 2000). Their extension sought variables that possibly better explain PU, such as subjective norm, image, job relevance, output quality, and result demonstrability (Marangunić & Granić, 2015; Venkatesh & Davis, 2000). Other models are based on the original research but include additional determinants and moderators for relationships such as the:

- UTAUT (Vanketesh et al, 2003),
- motivational model (Vallerand, 1997),
- TPB (Ajzen, 1991),
- model of information systems success model (DeLone & McLean, 1992),
- model of personal computer utilization (Thompson et al., 1991),
- innovation diffusion theory (Rogers, 2003), and
- social cognitive theory (Bandura, 1986).

Researchers such as Manis and Choi (2019) have developed models based on specific technologies such as virtual reality. The virtual reality hardware acceptance model adapts the TAM with a modified questionnaire but still found the constructs associated with TAM of PEU to have the highest relationship with the intention to use the technology.

The Relevance of TAM in Data-Driven Decision Making

The growing development and integration of technology in an end user’s private and professional life help decide to accept or reject technology (Marangunić & Granić, 2015). According to Sprenger and Schwaninger (2021), "the TAM is the most widely employed and best-known model to measure acceptance of various technologies" (p. 4). TAM is supported because of its robust nature in determining ATT (Alotaibi & Alajmi, 2021; Dixit & Prakash, 2018). Despite the development of many different variants that have demonstrated greater predictive values, TAM has shown through different meta-analyses to be the most widely applied theory regarding the acceptance and use of technology (Albarghouthi et al., 2020; Sánchez-Mena et al., 2017; Sholikah & Sutirman, 2020; Šumak et al., 2011).

TAM is most prevalent in e-learning technology studies but has also been successfully applied to technologies such as social media, virtual learning environments, mobile and digital libraries, learning analytics visualization, gamification of learning, LMS, and augmented reality (Sánchez-Prieto et al., 2020; Sprenger & Schwaninger, 2021; Šumak et al., 2011). TAM is also popular because it has been validated across many cultures (Sprenger & Schwaninger, 2021). According to a meta-analysis by Šumak et al. (2011), the most common research subject for TAM "is students, followed by employees and finally academics" (p. 2069).

TAM has retained its popularity because of the model's flexibility and ease of use (Sánchez-Prieto et al., 2020). Because TAM is easily measured through surveys based on the user's perceptions and is easily adaptable to other moderating factors, the model can be applied "to a wide variety of contexts and technologies" (Sánchez-Prieto et al., 2020, p. 81). Dumpit and Fernandez (2017) spoke to the robust nature of the model that allows the model to be applied to multiple types of technologies, not just computer systems. TAM also applies to the intent to continue using applications in education, not just future potential usage (Khamar Tazilah et al., 2021; Liu et al., 2003).

Because TAM was initially designed as a probability model for adopting technology by an individual or organization, the model is still relevant for organizations making decisions regarding technology adoption (Alfadda & Mahdi, 2021). BI is vital when predicting voluntary technology usage (Alamri et al., 2019). King and He (2006) provided a meta-analysis of 88 published studies demonstrating TAM as a robust model that can predict sufficiently accurately. Kim et al. (2021) gave credence to the number of studies that have confirmed the predictive powers. Sprenger and Schwaninger (2021) spoke to TAM's explanatory power and parsimony as to why TAM is still an influential model for technology acceptance despite the multitude of variations. PU captures much of the explanatory effect on BI, especially in hardware and productivity applications, while PEU adds an essential component in internet applications (King & He, 2006).

TAM also serves as guidance for educational technology leaders and educational administrators. TAM's parsimonious state gives straightforward advice on aiding technology adoption by making the new technology easy to use and straightforward communication of how the technology will aid in job performance (Sutton & DeSantis, 2017). Sánchez-Mena et al. (2017) explicitly applied the process of adoption of technology to education and noted "that teachers are the true agents of change in schools" (p. 356) and that adoption of new technology is highly dependent on the acceptance of teachers in the classroom. While many external factors influence an educator's decision regarding technology usage, the link between those factors is modeled in the TAM (Moodley et al., 2020; Šumak et al., 2011). Because it models the acceptance of technology applications so well, Akman and Turhan (2017) suggested that administrators could use TAM to provide data regarding potential weaknesses in implementing new technology.

The Relevance of TAM in Current Research

Finally, TAM is still relevant in recent research. Because of the link of the integration of technology in the improvement of teaching and learning research into individual motivation, the adoption of technology has become important (Cheng, 2019). Gan and Balakrishnan (2018) also toted TAM's popularity because of its predictive accuracy in recent research, especially in education. Its use demonstrates TAM's versatility as a reliable model and as a framework for research into the acceptance of innovative teaching practices, prediction of technology integration, exploration of technology adoption, and for comparison of technology adoption (Agyei & Voogt, 2011; Aldunate & Nussbaum, 2013; Martin-Garcia et al., 2019; Salinas et al., 2016). Many regional studies have confirmed TAM as a model for student acceptance of online learning in higher education (Khamar Tazilah et al., 2021; Raman, 2011; Wong et al., 2013). Researchers such as Daher et al. (2021) chose to use TAM because of its ability to fit pedagogical frameworks.

TAM has a much stronger explanatory power when researching technology acceptance by students while explaining around 50% of the variation in the model (Farooq et al., 2021). In the model's early days, TAM was "the most influential, commonly employed, and highly predictive model of IT adoption" (Fathema et al., 2015, p. 212) and was primarily used in business applications. Extended research investigating e-learning acceptance during the last decade has led to a resurgence of publications with TAM as an explanatory model (Fathema et al., 2015). TAM is also attractive in research because of its parsimony and predictive accuracy in that more recent derivations such as UTAUT2, which has seven factors and three moderators, only increase explanatory power marginally (Alfadda & Mahdi, 2021; Gan & Balakrishnan, 2018; Sprenger & Schwaninger, 2021). TAM is also attractive to researchers because the sample sizes necessary for significance testing are conveniently small (King & He, 2006).

Digital Transformation of Higher Education

According to Vial (2019), DXs are inherently disruptive in three primary areas: “consumer behavior and expectations, competitive landscape, and the availability of data” (p.

122). Digital technologies profoundly impact the behavior and expectations of consumers, who become active participants in the relationship between the organization and its stakeholders (Vial, 2019). In this application, a DX would occur when LMS are seen by higher education faculty as a primary means of instruction and communication with students. Digital technologies disrupt the current markets when they offer a combination of services or provide new digital services that lower acceptance barriers, making previous offerings challenging to sustain (Vial, 2019). LMS would be seen in this framework as a DX when it is easier to distribute instruction through digital and innovative methods than traditional instructional methods. Finally, digital technologies foster the generation of actionable data to better improve their services to the consumer (Vial, 2019). LMS generate massive digital footprints regarding student learning activities and engagement.

According to Vial (2019), inertia and resistance are the primary barriers to DX. Inertia towards a path builds upon the reliance on procedures and processes that are not easily reconfigured and can often be rigid (Vial, 2019). Resistance is based on the employees' resistance to change towards digital technology and can be based on “innovation fatigue” (Fitzgerald et al., 2013) or an extreme disruption to a culture that is perceived as unacceptable (Vial, 2019).

Rubene et al. (2021) argued that education has been resistant to a widespread DX prior to COVID-19 for various reasons: financial support, technological support, negative ATT, the potential impact on educational policy, or resistance to shifting to student-centered learning practices. According to Rubene et al. (2021), the COVID-19 global pandemic allowed faculty and administrators to overlook the reasons for the resistance to DX and forced higher education to invest heavily in the financial resources, infrastructure, and learning events necessary to enhance students' remote learning experiences.

LMS Overview

The history of LMS predates the pervasive use of personal computers into the 1950s (Watson & Watson, 2007). However, it has been known by other names, such as integrated learning systems (ILS), where computers began to provide the functionality of providing access to instructional content and management and cohesive integration of instructional tools (Bradley, 2021; Watson & Watson, 2007). Over time as technology applications developed, digital media and communication tools were incorporated, which helped increase learner choice (Bradley, 2021). The development of multimedia web applications accelerated the development of LMS (Correia et al., 2018). Because of tools such as LMS, modern education is no longer confined to traditional classrooms (Balaman & Bas, 2021).

LMS serve as a distribution staging site for pedagogical materials that meet designed learning objectives (Bradley, 2021; Watson & Watson, 2007). LMS platforms embed digital educational activities and resources into course structures (Milosevic et al., 2014). An LMS fosters engagement with learners, allowing them to submit work for assessment, track learning progress, receive updates to the content, interact with other learners at a distance, syllabi tools, student progress tracking tools, self-paced learning, and receive course announcements (Al-Fraihat et al., 2020; Balaman & Bas, 2021; Bradley, 2021; Watson & Watson, 2007). Web-based online learning has helped grow "the quality, content, and scope of education" (Balaman & Bas, 2021, p. 2).

An LMS can enhance asynchronous and synchronous learning in higher education (Prasetyo et al., 2021). Synchronous learning can be empowered by providing support to live lectures and real-time interaction between students and lecturers (Ejdys & Kozlowska, 2021; Littlefield, 2020). Asynchronous learning involves the availability of learning materials (e.g., video, tutorials, readings) and interactions between students and lecturers through non-real-time interactions such as discussion boards, announcements, or wikis (Ejdys & Kozlowska, 2021; Littlefield, 2020). Asynchronous or synchronous learning methods are well supported by modern LMS using resources available to the instructor, such as Zoom or Google Meet (Işikgöz, 2021).

An LMS provides flexibility that allows faculty to build interactive lessons based on sound pedagogical principles (Bradley, 2021; Watson & Watson, 2007). LMS platforms help support and simplify pedagogically sound principles such as instructional management, interactive feedback processes, interactive content, and immediacy of learning (Balaman & Bas, 2021). Taat and Francis (2020) demonstrated that online learning could improve learning performance and productivity, which positively influences acceptance and, in turn, promotes the effectiveness of online learning (Khamar Tazilah et al., 2021).

LMS benefit the learning environment for teachers, learners, and administrators (Correia et al., 2018). Educational administrators can use the LMS to assist in the automation, reporting, and evaluation of the learning process (Correia et al., 2018).

Ejdys and Kozlowska (2021) state that, despite LMS platforms' effort to add features and technology developments, an LMS is still highly dependent on acceptance by its users, and all too often, they are rejected (Recker, 2016). Students often have a negative attitude toward online learning and perceive it as not easy to use (Khamar Tazilah et al., 2021). According to Alamri et al. (2019), an LMS perceived as easy to use is more likely to be accepted even when the performance benefits may be higher. When students have been demonstrated how an LMS can aid them in their learning performance through access to online learning, they hope that they can accept the use of LMS in their coursework (Khamar Tazilah et al., 2021).

Learning Management System Benefits

The benefits and skills, such as digital literacy and individualization, of learning that are taught through the abilities of an LMS give credence to the positive attributes of online learning in higher education (Ejdys & Kozlowska, 2021). According to Dhawan (2020), when used properly, online learning through an LMS can be a tool that makes "the teaching-learning process more student-centered, more innovative, and even more flexible" (p. 6). Almazova et al. (2020) note the potential of online learning environments to enhance the efficacy of knowledge, foster critical thinking, develop self-learning, and progress information processing skills. At the very minimum, the use of LMS provides increased efficiency for faculty to teach and learn in convenient environments and at convenient times (Leoste et al., 2021)

Using an LMS platform also helps shift learning from passive to active learning (Balaman & Bas, 2021). The accessibility of education and “the capability of developing, gathering, delivering, and integrating the necessary information, skills and competence in the field of their personal interest or occupational needs” (Balaman & Bas, 2021, p. 2) is a crucial determinant in the future success of individuals. According to Ramasamy et al. (2021), the emphasis on interactive technology-based learning practices improved higher education students' learning capacity and productivity in a knowledge-based society. These interactive learning experiences allow individualization of learning and access (Rubene et al., 2021).

According to Al-Maroof et al. (2021), e-learning platforms have been demonstrated as an effective means of communication in educational institutions, and those institutions that instituted the change to online learning during COVID-19 have demonstrated that they are not only safe and effective but that they helped institutions meet their learning objectives. Alturise (2020) speaks to an LMS's effectiveness in providing the university with a shared remote interface for faculty and students to attend lectures, submit and assess assignments, and proctor quizzes. The communication facilitated by an LMS between faculty and students allows both to access course content remotely with internet access (Alturise, 2020).

An LMS ensures the efficient delivery of educational content in a digital format in contrast to a traditional model while reducing the reliance on paper and physical textbooks and thus reducing environmental impact (Alturise, 2020).

Challenges With Online Learning and LMS

Instructional methodology in an online environment differs significantly from conventional teaching forms (Almazova et al., 2020). The ability to teach online successfully and efficiently is not solely predicted by subject matter knowledge and computer literacy (Almazova et al., 2020). Higher education's reliance on outsourced content developers highlighted the lack of competency in developing online learning environments (Almazova et al., 2020; Houldon & Veletsianos, 2020). Any transition to online learning, but especially the abrupt transition during COVID-19, faces the challenges of technological infrastructure and support, inexperience with digital tools, and a lack of online pedagogical training (Dindar et al., 2021). Schools and faculty that fail to address these challenges during a transition will cause increased workload and stress on faculty, causing students to feel a difference in the quality of pandemic-time education (Dindar et al., 2021). Online learning also has risks for less mature students, those lacking internal motivation, students with learning difficulties, and students from economically disadvantaged homes (Rubene et al., 2021).

Calls for Further Research on TAM

Dhawan (2020) calls for due diligence amid the chaos and tensions of this pandemic. Sukendro et al. (2020) call for future research on the effects of the outbreak on distance learning practices across multiple populations, regions, and content areas. King and He (2006) note that students are most often the subjects of studies because they are a convenient sample, but research has demonstrated that professionals and general users produce different results (Ejdys & Kozlowska, 2021). There is a lack of literature on faculty acceptance, especially across multiple disciplines (Ejdys & Kozlowska, 2021).

Alhumaid et al. (2021) also call for additional research on the acceptance of learning systems because of the educational system's reaction to the pandemic to garner a complete picture regarding the implementation of systems. Raza et al. (2021) believe that further e-learning technology acceptance research is crucial for decision-makers as any investment in these infrastructures is significant.

Additional research has also been called to identify additional moderating factors in the model (Marangunić & Granić, 2015). Balaman and Bas (2021) call for additional research across various e-learning environments and different learning environments. According to Dindar et al. (2021), "technology acceptance is not a one-time process, and occurs over time" (p. 3). It is vital to continue studying technology acceptance by examining different technologies, mitigating factors, and circumstances, such as COVID-19.

Finally, Sangeeta and Tandon (2020) call for additional research across multiple regions because localized studies like theirs may not be generalizable to all populations. Işikgöz (2021) calls for additional research in larger sample sizes and quantitative studies because of the localized nature of most research on this topic.

Summary

This chapter reviews the literature on the TAM, LMS, and the impact of COVID-19 on higher education technology acceptance. The chapter began with a review of the literature search methods. Information was then provided on the TAM, which serves as the study's theoretical framework. The main body of literature included research on technology acceptance in education, the advantages and disadvantages of LMS, and the impact of the COVID-19 global pandemic on pedagogical practices in higher education concerning technology acceptance. The information gleaned from the literature review is used to inform the design and methodology chosen for the present study, which is presented in Chapter 3.

Chapter 3: Research Method

The objective of this non-experimental multiple regression study was to gain an understanding of a potential change in the mindset of how university faculty perceive LMS and whether faculty intentions (to begin to using or continue using LMS) changed following the shift to online learning during the global COVID-19 pandemic.

This chapter presents the study's methodology including a detailed description of the research design. Also included is a discussion of the sample population, the data collection methods, and the data analysis protocol. The central question of this quantitative study asked: What is the impact of higher education institutions' response to COVID-19 on faculty acceptance of learning management systems? To answer this question, four research questions framed the investigation.

RQ1: What is the effect of COVID-19 protocols on the perceived ease of use of learning management systems in higher education?

RQ2: What is the effect of COVID-19 protocols on the perceived usefulness of learning management systems in higher education?

RQ3: What are the perceptions of higher education faculty regarding their behavioral intent to use learning management systems during COVID-19?

RQ4: Has perceived acceptance of learning management systems changed for higher education faculty since COVID-19?

Research Design and Method

The TAM has long been validated as an appropriate model for assessing a user's acceptance and intent to use technology in various circumstances, including education (Al-Fraihat et al., 2020; Davis, 1989; Manis & Choi, 2019). The TAM is modeled through structural equation modeling because of the multivariate complexity of the model (Al-Fraihat et al., 2020; Hair, 2006). Structural equation modeling is a popular statistical methodology because of its flexibility and the ability of software to accommodate nonstandard conditions of the data (Kaplan, 2012).

The data from this study were derived from an anonymous online survey delivered to lists of higher education faculty who fulfilled the desired sample population. According to Vehovar and Manfreda (2011), online surveys based on standardized and validated questionnaires have become an essential tool for research fields. Self-reported data collected through surveys is a fundamental stalwart as a research tool, especially in the social sciences (Fryer & Nakao, 2020).

In the study, I deployed a 20-question survey to gather quantitative data on higher education faculty members' PU, PEU, ATT, and BI to use or continue using LMS. Survey methods enabled me to quantify the mitigating factor (i.e., outside risk factor of COVID-19) unlike some prior TAM research that relied on qualitative methods (i.e., interviews or observations). The sample of research participants were from multiple higher education institutions and had diverse experiences, beliefs, and ATT of LMS, which provided credibility to the research.

The survey was developed and made available to participants on Qualtrics XM, a web-based survey solution that provides the means to articulate and host the web-based survey, collect the response data anonymously, and perform a preliminary analysis of the data. A pilot study was conducted before finalizing the formal survey. The knowledge gained from the pilot study provided the information necessary to modify the final survey.

Pilot Study

To enhance content validity, Davis (1989) suggested using a pilot study, allowing items to be eliminated or modified. Other researchers (Alhumaid, 2021) support this practice and suggest the sample size of the pilot study to be approximately 10% of the desired sample size, which was approximately 25 participants for this study. The pilot study was used to reveal potential deficiencies in the proposed design of the study. After the initial analysis of the survey data using a set of plugins to SPSS, the data were evaluated for analysis with structural equation modeling.

Population

The population under consideration was faculty from higher education institutions worldwide. The target population was faculty who evaluated their use of LMS over the last two years as either a new pedagogical methodology or as a continuance of their previous pedagogical choices.

Study Sample

Subjects came from a multistage cluster sampling methodology (Taherdoost, 2016). The cluster sampling methodology allowed for random sampling by dividing the population into homogeneous groups based on a characteristic such as geography or, in this case, the digital contact method. Cluster sampling can be challenging to implement for web-based surveys as it often requires ancillary data regarding the sampling population (Fricker, 2011). In this case, the ancillary data were participation in listserv and Facebook groups relating to technology usage and exploration of pedagogy in higher education.

The first group of clusters was faculty from EDUCAUSE member institutions. EDUCAUSE has an active membership of over 114,081, with members at 1,423 US institutions and 194 international institutions (EDUCAUSE, 2021). Of those members, 11,809 self-identify as faculty members (EDUCAUSE, 2021). Within this group, multiple list services have demonstrated active engagement surrounding the use of technology in higher education. Each member of the identified groups was delivered an email (see Appendix A) through the listserv that delivered some fundamental information regarding the survey tool and a link to the online survey tool. The identified Educause listservs that met the criteria for the research were groups titled Blended and Online Learning, Digital Transformation, Instructional Design, and Instructional Technologies.

The second group of clusters was Facebook groups dedicated to faculty concerned with their response to pedagogy during the global pandemic and groups of faculty and higher education professionals that focus on the use of educational technology in higher education. Groups such as Pandemic Pedagogy, with over 32,000 faculty members (Pandemic Pedagogy, 2021), have been very active over the last two years and have been responsive to similar calls for research. The groups that were sent the solicitation for research posts (see Appendix B) were: Pandemic Pedagogy, EDUCATION TECHNOLOGY, Higher Ed Learning Collective, and LMS.

Materials/Instruments

The survey (see Appendix C) was a modification of the TAM survey first developed by Davis (1989) and then modified later by Alharbi and Drew (2014) for LMS. The modifications by Alharbi and Drew (2014) demonstrated a high level of internal consistency and reliability with a Cronbach alpha value exceeding the necessary value of 0.07, with all scales exceeding 0.70. I obtained permission from authors of the research tool before progressing with the research (see Appendix D.)

The survey contained four sections. The first section collected consent to participate in the study and verified that interested faculty met the criteria for the study. The second section collected demographic data regarding the faculty member, to include experience with LMS, the characteristics of their institution, and the LMS their institution uses, if any. The third section used 7-point Likert matrix questions to measure TAM constructions that ranged from strongly disagree to strongly agree. The TAM constructs included were PEU (7 items), PU (6 items), ATT (3 items), BI (2 items), and job relevance (2 items). The final section used a Likert question to measure the perceived effect of COVID-19 protocols on the acceptance of LMS. The text of the survey is included in Appendix C.

Data Collection and Analysis Procedures

Participation in the anonymous online survey was solicited through email by listservs and posting to the Facebook group page. The desired sample size was based on a research consensus for an SEM-saturated model. According to Schumacker and Lomax (2010), "a saturated model with p observed variables has $p(p+3)/2$ free parameters" (p. 41). Schumacker and Lomax suggested that a small sample size does not provide sufficient degrees of freedom to correctly estimate the model given many variables. Researchers do not agree on the ideal sample size for an SEM analysis. For example, some suggest a sample size as low as 100 to 150 subjects (Ding et al., 1995) while others assert that 5,000 subjects are insufficient (Hu et al., 1992). Schumacker and Lomax suggest that the model will likely be validated with a sample size between 250 to 500 subjects—following a ratio of 10 subjects per variable based on the broad consensus of work. With a survey length designed to measure five variables, the desired sample size for my study was at least 100 participants. The primary work conducted after analysis to fit the SEM was completed using IBM's SPSS Amos software. IBM SPSS Amos is a standalone software program used to extend standard multivariate analysis methods including the SEM and path analysis.

Demographics Measure

After a consent agreement, the second section of the survey tool collected demographic data from survey participants. Demographic information captured from each subject was used to support a correlational analysis between each variable. Demographics expanded the examination of personal characteristics and their impact on the acceptance of LMS. Demographics collected by the survey tool included the following: whether faculty were already using an LMS or began using an LMS during COVID-19, current academic rank, gender, faculty experience in higher education, faculty experience at their current institution, experience with any LMS, and identifying which LMS the faculty member is currently using at their institution.

Measuring TAM Constructs

The third section of the survey tool was a measurement of the TAM constructs PEU (6 questions), PU (6 questions), perceived ATT (3 questions), and perceived BI (2 questions). These survey questions were initially developed and validated by Davis (1989) to assess the perceptions of users based on a seven-point scale ranging from 1 (Strongly Disagree) to 7 (Strongly Agree). Alharbi and Drew (2014) modified the questions to analyze perceptions regarding LMS usage, and one additional question was added to measure the perceived effect of inexperience on PEU.

Effect of COVID-19 Protocols

One additional section (3 questions) in a similar style to the TAM constructs was added to measure potential effects of COVID-19 protocols on the TAM constructs of PEU and PU and whether participants already felt comfortable using an LMS before COVID-19. The pilot study was implemented to evaluate the validity of this section of questions.

Ethical Considerations

Informed consent was gained from all participants by providing an opening page to the survey with a question to obtain permission to use their information. If the participants did not consent, they were automatically disqualified from participating in the study. The informed consent page ensured that participants understood the intent of the survey, and it also explained the terms of confidentiality, protocols, and detailed potential risks associated with the study. This consent page also provided contact information in the event that a participant wished to make an inquiry to me or the Institutional Review Board chair (see Appendix E). The survey collected information anonymously, and no identifying data were collected or retained.

Assumptions

Because the SEM is a correlational analysis method, similar conditions can affect the variance or covariance among variables, which may impact the modeling analysis (Schumacker & Lomax, 2010). Several conditions must be met to apply SEM analysis with fidelity. The data were checked for outliers, nonlinearity, and nonnormality. These checks can be applied using modified box plots for outliers, scatterplots for nonlinearity, and histograms for nonnormality (Schumacker & Lomax, 2010).

It is assumed that the findings in this observational study were based on higher education faculty currently using an LMS or investigating an LMS during COVID-19. Without further research, these findings should not be generalized to all instructors outside of sample or to perceived attitudes regarding other technologies.

It is assumed that all faculty participants are using an LMS for a course in which they are officially the instructor of record. It is also assumed that the study participants answered all survey questions openly and honestly.

Limitations and Delimitations

This study provided a conceptual framework for faculty acceptance of LMS in higher education in light of a global pandemic that forced many faculty members to use the same software to communicate with their students. The data were derived from cluster samples from multiple higher education institutions. This survey design lends itself for generalizability beyond the immediate surveyed population.

Limitations are factors that could potentially affect the research outcome and over which the researcher does not have control (Roberts & Hyatt, 2019). A potential limitation of the study is that participants who respond to the survey may have intense emotions regarding the use of LMS in higher education; thus, they may be overrepresented in the sample. Additionally, respondents may be victims of survivor bias as they made it through teaching during COVID while others did not (Lockwood, 2021). Finally, participants may over- or underrepresent their use of LMS and their actual perceptions.

Delimitations are factors that could potentially affect the outcome of the research over which the researcher does have some semblance of control (Roberts & Hyatt, 2019). A delimitation of this study is that all data were collected through self-reported surveys of the participants' perceptions. Another delimitation is that participants' actual usage of LMS cannot be investigated (even though it is one of the TAM constructs) because of the research timeline and the anonymity of the survey tool. This study only examines one type of technology that could have been adopted during COVID-19; thus, other technology types should not be generalized based on these findings. Another delimitation is that only one TAM was analyzed although other models might have been a better fit. Also, all participants were required to use an LMS even though some other modalities for online might be better suited.

Summary

This chapter presented a detailed description of the proposed study design, the rationale for selecting the research methods, and the instruments used to analyze those data to answer the research questions.

Chapter 4: Results

This study employed a quantitative research design to determine the impact of higher education's institutional responses to COVID-19 on faculty acceptance of LMS. For the semesters following the onset of the global pandemic, higher education faculty were forced to use LMS to complete the semester in remote learning, teach during government-imposed shutdowns, and communicate with students during quarantines. This chapter presents the findings from the analysis of the survey regarding perceptions and ATT surrounding LMS. The first section reviews the statistical procedures performed by cleaning the data, assessing missing data, and assessing the normality of the data sets in preparation for the quantitative analysis. Procedures for establishing the validity and reliability of the additional constructs and descriptive analyses are also discussed. Next, findings from the research questions are presented by providing the results from the confirmatory factor analysis and the SEM. The chapter then closes with a summary of the findings of the research questions.

Quantitative Data Analysis and Results

This section provides the findings from this research study. The data for this section were collected through an online survey in Qualtrics that was emailed to several listservs and posted in Facebook higher education faculty groups. The purpose of the survey was to gather demographic information on the participants and determine their perceptions of their current ATT of LMS, the effect of COVID-19 protocols on those attitudes, and the future intent to use LMS for instructional purposes.

A total of 139 responses to the survey were screened before analyzing the data. Multiple descriptive analyses were conducted to describe the population being analyzed and to determine whether perceptions of the effect of COVID-19 protocols were a mediating factor in the TAM regarding the use of LMS. Confirmatory factor analysis was employed to consider the constructs' validity and the theoretical model's goodness of fit. Structural equation modeling was used to identify and quantify relationships. This statistical analysis employed through exploratory and confirmatory factor analysis of structural equation modeling was used to answer the research questions of this study:

RQ1: What is the effect of COVID-19 protocols on the perceived ease of use of learning management systems in higher education?

RQ2: What is the effect of COVID-19 protocols on the perceived usefulness of learning management systems in higher education?

RQ3: What are the perceptions of higher education faculty regarding the behavioral intent to use learning management systems during COVID-19?

RQ4: Has perceived acceptance of learning management systems changed for higher education faculty since COVID-19?

Pilot Study

Before the actual study, a pilot study was performed to test the validity of the survey instrument as a modification of previously used survey tools. A link to an online questionnaire was sent via email to faculty randomly selected individuals from the list of full-time faculty at Abilene Christian University. One follow-up email was sent a week after the original email to encourage additional responses. A total of 22 faculty completed the instrument to assess the validity and the time the survey took to complete. Verbal feedback was received from one of the participants on the readability of the questions to help improve the survey tool. The results were used to test for reliability and validity and to improve the survey.

Pilot Study Analysis

Because the instrument was a combination of previously validated and originally designed constructs, a pilot study was essential to measure the instrument's reliability. In order to test the reliability of each latent variable, Cronbach's coefficient alpha of 0.70 ($\alpha > 0.70$) was used as the threshold, as suggested by Taber (2018). With the exceptions of BI and the Effect of COVID-19 (COV), each of the α values were greater than 0.7, which indicated that all of the reliability scores were acceptable. Further, all of the α values were greater than 0.8, indicating the tools are highly reliable as shown below in Table 1. The 95% confidence interval, as suggested by Bravo and Potvin (1991) demonstrated that the population would also be acceptable (see Table 1). Also included in the analysis were any α values that would increase if an individual item was deleted beyond the confidence interval, indicating that the item detracted from the tool's reliability (see Table 1).

Table 1

Reliability Scores for the Pilot Study

			95% CI		
Variables	*N*	α	*LL*	*UL*	α if Deleted
Perceived Ease of Use (PEU)	7	0.855	0.735	0.933	0.962
Perceived Usefulness (PU)	6	0.967	0.939	0.984	N/A
Attitude Toward Technology Use (ATT)	3	0.994	0.989	0.998	N/A
Behavioral Intention (BI)	2	0.501	-0.231	0.797	---
Effect of COVID-19 Protocols (COVID)	3	0.619	0.226	0.830	0.896

Note. N = number of questions analyzed; N/A = not applicable as no values returned that were higher than the base α value; --- = not measured.

Because the variables of PEU and COVID had items that would have increased their reliability, those items were removed from the item analysis and did not contribute to the variable being measured; however, these variables were retained in the survey tool as potential population filters. The questions that were removed from the tool were, "I feel that my ability to determine LMS ease of use is limited by my lack of experience" (PEU subset) and "Before the COVID shutdown, I was already a proficient LMS user" (COVID subset).

Because the variable of behavioral intent then had only one observed endogenous variable in the first behavioral intent question, "I plan to use/ continue to use an LMS in the future," the SEM could not be used to map this endogenous variable to the unobserved exogenous variable of behavioral intent. Nevertheless, this unit was still measured in the event that it could be used later in the model.

Data Screening

The survey data were examined through visual means and descriptive statistics for missing data and the identification of outliers. Of 139 participants who began the survey in Qualtrics, 18 incomplete responses were observed. These occurred because those participants failed to complete all the questions/items in the survey. The 18 participants with incomplete responses were removed from the final sample. A standard deviation analysis was performed of the Likert-style questions. While nine of the results demonstrated little to no variation in their responses to these questions, the demonstrated variability in previous demographic questions led to the acceptance of these as complete and honest responses to be included in the analysis.

Assessment of SEM Assumptions

Six conditions for the SEM may potentially impact the analysis (Schumacker & Lomax, 2010). According to Schumacker and Lomax (2010), because SEM is a correlational research method, the conditions regarding "the measurement scale, restriction of range in the data values, missing data, outliers, nonlinearity, and nonnormality of data" are potential issues concerning the covariance between variables and should be addressed (p. 29).

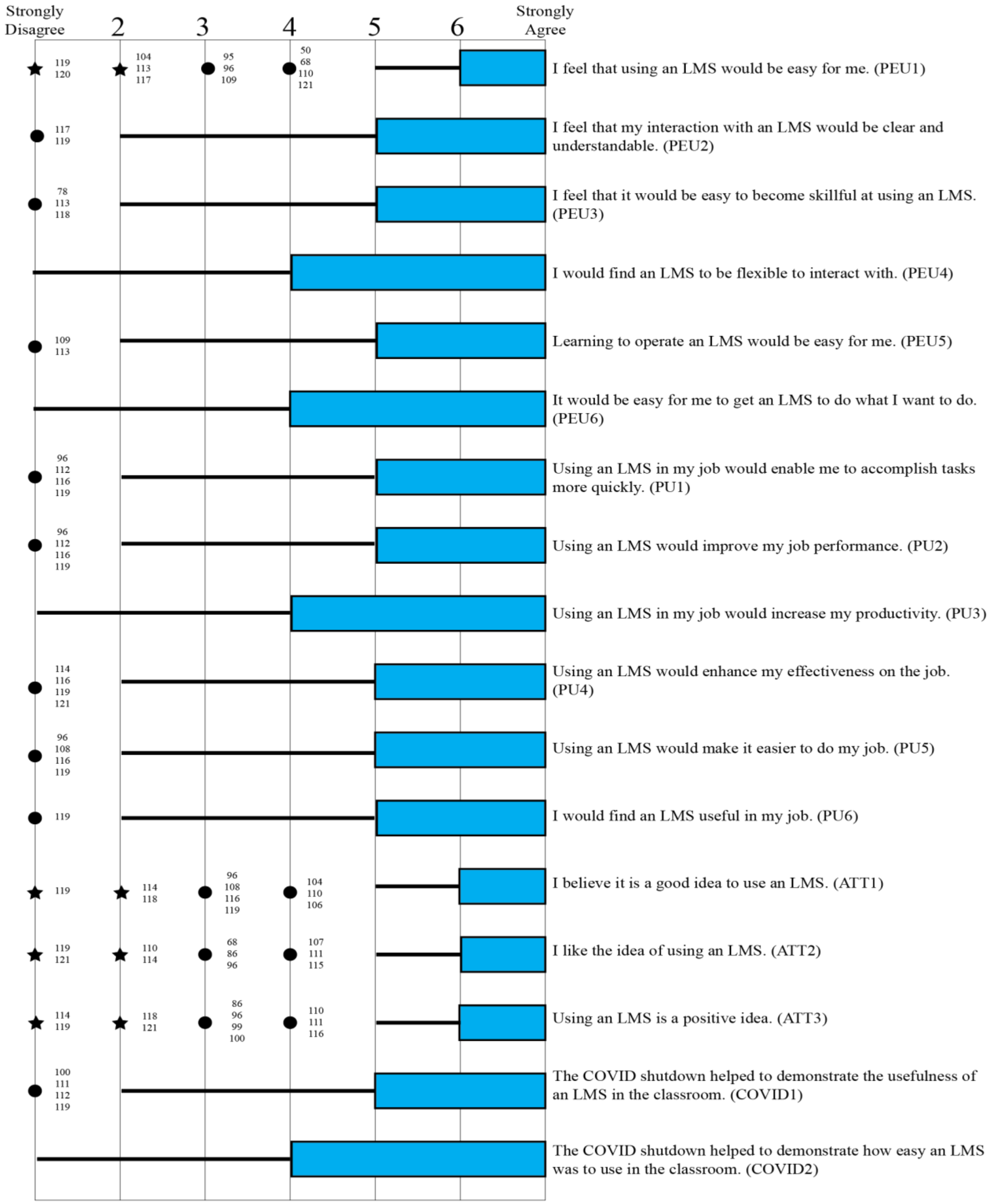
The first two conditions are addressed through the research methodology in that the survey questions are ordinal Likert-scale questions that are often treated as interval data in educational technology research. However, nonparametric tests were used to check for normality (Chen & Liu, 2020). Because the data were ordinal data with a limited range of 1–7, some of the validity of this construct and theoretical model are under question as the data did not meet the requirements of continuous data. Any research conclusions from noncontinuous data would ordinarily be met with question; however, because the original theoretical model was developed based on the same survey questions as this research, it is reasonable to proceed using this analysis method (Venkatesh & Davis, 1996).

The third condition of missing data values was addressed in this data through mean substitution when only some of the data values were missing from a response. Schumacker and Lomax (2010) suggested that "mean substitution works best when only a small number of missing values is present in data" (p. 20). In this case, no more than two values needed to be substituted with any variable, while most required no substitution.

When assessing the fourth condition of outliers, all but five variables included in the theoretical model generated multiple outliers. Figure 2 displays a boxplot generated in SPSS that illustrates both outliers and extreme outliers of the distributions labeled with the case numbers. The number of outliers seems to be present because of the skewed nature of the distributions. This skewed nature of the distributions confirms the proposed theoretical model because faculty demonstrate a propensity to rate each of the variables high, including acceptance of LMS.

Figure 2

Boxplots of the Endogenous Likert Type Variables Used in the Model



The fifth condition of nonlinearity was addressed through ordinal regression in SPSS. In the chi-square test for model fitting information, there is a statistically significant result that the model is a significant improvement in the fit of the final model over the null or intercept-only model [$\chi^2(101) = 133.423, p = 0.017$]. The Goodness of Fit table contains the Deviance and Pearson chi-square tests, which are useful for determining whether a model exhibits a good fit to the data. Non-significant test results are indicators that the model fits the data well (Field, 2017). In this analysis, we see that both the Pearson chi-square test [$\chi^2(347) = .178, p = 1.000$] and the deviance test [$\chi^2(347) = .354, p = 1.000$] were both non-significant. These results suggest a good model fit. When the result of the test of parallel lines indicates non-significance, it is interpreted to mean that the assumption is satisfied. Statistical significance is taken as an indicator that the assumption is not satisfied (Osborne, 2017). In this analysis, the results can be interpreted that the assumption is satisfied [$\chi^2(303) = .000, p = 1.000$]. By meeting each of these assumptions for linearity, the data can be fitted with a linear model.

The sixth and final condition of normality of data demonstrated that the distributions were not normal. Histograms of the distributions demonstrated strong skewness in each distribution towards smaller numbers. The distributions also reflected this lack of normality when the trimmed means were not within a 90% confidence interval of the mean. A Shapiro-Wilk test for normality produced a significant result, with each variable rejecting the null hypothesis of a normally distributed population, as demonstrated in Table 2 below.

Table 2

Tests for Normality of the Likert Variables Used in the Model

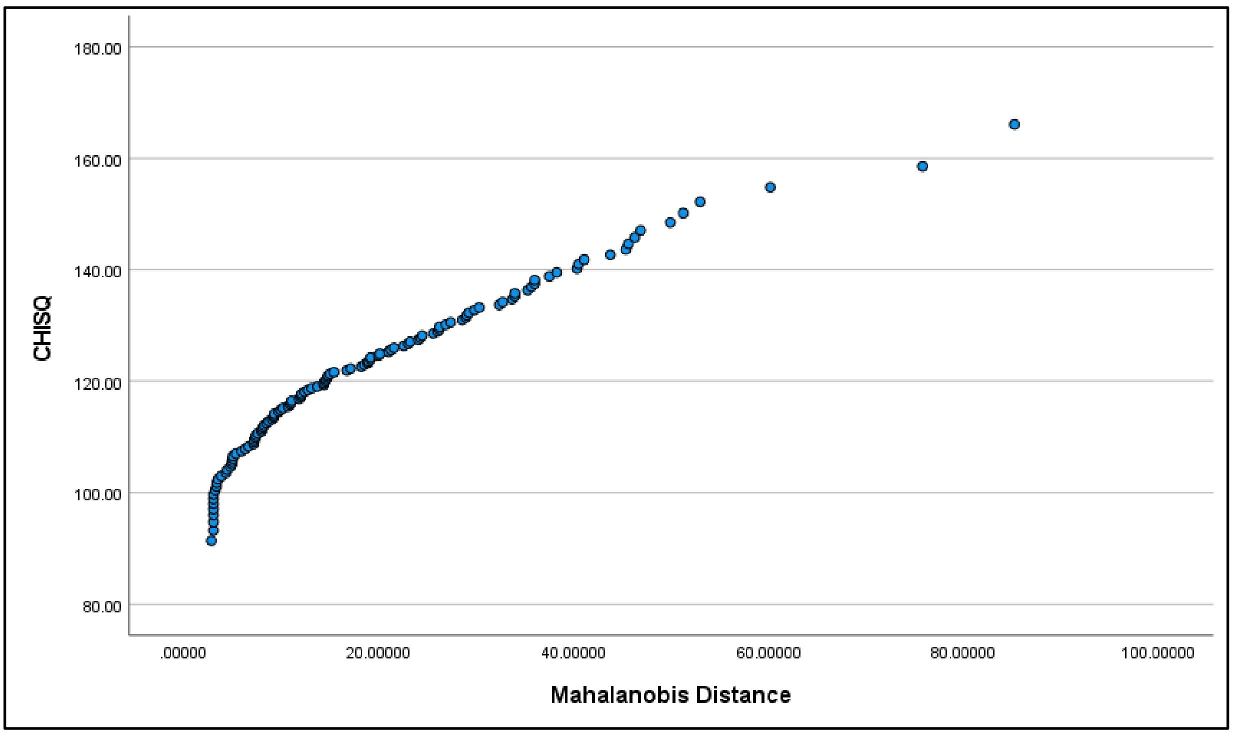
Survey questions	Shapiro-Wilk		
	Statistic	*df*	Sig.
I feel using an LMS would be easy for me.	.701	119	.000
I feel my interaction with an LMS would be clear and understandable.	.764	119	.000
I feel that it would be easy to become skillful at using an LMS.	.840	119	.000
I would find an LMS to be flexible to interact with.	.885	119	.000
Learning to operate an LMS would be easy for me.	.801	119	.000
It would be easy for me to get an LMS to do what I want to do.	.896	119	.000
Using an LMS in my job would enable me to accomplish tasks faster.	.798	119	.000
Using an LMS would improve my job performance.	.828	119	.000
Using an LMS in my job would increase my productivity.	.856	119	.000
Using an LMS would enhance my effectiveness on the job.	.796	119	.000
Using an LMS would make it easier to do my job.	.818	119	.000
I would find an LMS useful in my job.	.717	119	.000
I believe it is a good idea to use an LMS.	.589	119	.000
I like the idea of using an LMS.	.695	119	.000
Using an LMS is a positive idea.	.695	119	.000
The COVID shutdown helped demonstrate the usefulness of an LMS in the classroom.	.743	119	.000
The COVID shutdowns helped demonstrate how easy an LMS was to use in the classroom.	.883	119	.000

Note. All p values were significant ($p < .0001$, $N = 121$, $df = 119$), which implies non-normality.

Since the individual variables failed to verify the normal distributions used in the analysis, a multivariate normality assessment was used. This approach used Mahalanobis distances calculated in SPSS multivariate linear regression plotted against chi-squared values in a scatterplot to verify linearity (Arifin, 2015; Burdenski, 2000). This process produced a roughly linear plot with some curvature near the lower end. As seen in Figure 3, a linear regression t-test was significant at the $p < .001$ level.

Figure 3

Mahalanobis Distance vs. Chi-Squared Values for Check of Normality



Because two of the six conditions were not met for use in developing an SEM, a large enough *n* was collected to satisfy the criteria for SEMs, following the general rule of thumb of 10 to 20 samples per variable (Schumacker & Lomax, 2010). This theoretical model contains five variables and surpasses the required sample size at $n = 121$.

Demographics of the Sample

Based on the research questions, this study's desired population was higher education faculty that had analyzed or had used an LMS since the onset of COVID-19. Because the survey was distributed through faculty communications and faculty-focused social media groups, there was a wide variety of responses amongst varying demographics. Likewise, because the survey was not sent to a specific population, the response rate of those who viewed the survey was indeterminate, although the potential viewership of the survey invitation at the time of sending the survey was approximately 94,400 based on group memberships published at the time.

The social media groups from Facebook and their estimated memberships were Pandemic Pedagogy (32K), Pandemic Pedagogy (6K), Education Technology (3.4K), Higher Ed Learning Collective (41.8K), and Learning Management System (5.0K). The EDUCAUSE groups that were sent the survey invitation through a list-serv, and their estimated memberships were Blended and Online Learning (1.6K), Digital Transformation (1.1K), Instructional Design (1.5K), and Instructional Technologies (2K).

Various socio-demographic questions were asked to help answer the research questions and provide a generalizability justification of the research tool. The survey helped to identify gender identification, current academic rank, cumulative faculty level of experience, faculty experience at the current institution, experience with using an LMS, whether faculty were currently teaching, and current LMS being used at the institution.

The socio-demographic information communicated a wide variety of members that would represent a random sample of the population. Two areas of concern were the gender discrepancy, where females seem to be overrepresented, and the overrepresentation of faculty with experience. Table 3 displays a summary of demographic responses to the survey.

Table 3

Summary of Demographic Responses to Survey

Socio-demographic categories	Descriptions	Count	%
Gender	Male	23	19.0
	Female	94	77.7
	Prefer to self-describe	2	1.7
	Prefer not to answer	2	1.7
Current Academic Rank	Professor	27	22.3
	Associate Professor	29	24.0
	Assistant Professor	15	12.3
	Lecturer	16	13.2
	Instructor	19	15.7
	Adjunct	4	3.3
	Other	11	9.2
Cumulative Years of Experience	At least 1 year and less than 3 years	1	0.8
	At least 3 years and less than 5 years	5	4.1
	At least 5 years and less than 10 years	23	19.0
	At least 10 years	91	75.2
	Unanswered	1	0.8
Experience at Current Institution	Less than 1 year	3	2.5
	At least 1 year and less than 3 years	9	7.4
	At least 3 years and less than 5 years	14	11.6
	At least 5 years and less than 10 years	23	19.0
	At least 10 years	72	59.5
Experience Using an LMS	At least 1 year and less than 3 years	6	5.0
	At least 3 years and less than 5 years	7	5.8
	At least 5 years	105	86.8
	Unanswered	3	2.5
Current Teaching Status	Currently teaching	109	90.1
	Last taught less than 1 year ago	7	5.8
	Last taught between 1 – 2 years ago	3	2.5
	Last taught more than 2 years ago	2	1.7
Current LMS Used at Institution	Canvas by Instructure	65	53.7
	Blackboard	31	25.6
	Moodle	23	19.0
	D2L Brightspace	19	15.7
	Google Classroom	3	2.5
	Sakai	3	2.5
	Other	5	4.1

Note. Current LMS used at the institution included multiple selections of all that applied.

Exploratory Factor Analysis

Once the data were screened and processed for socio-demographic information, the next step was to perform an exploratory factor of analysis to verify that the questions fit into the factors of the hypothesized model and determine whether the model's covariance led to a plausible relationship within the constructs of the model (Reio & Shuck, 2014). The suitability of factor analysis was determined by two criteria: (a) the Kaiser-Meyer-Olkin measure of sampling adequacy, and (b) Bartlett's test of sphericity.

Kaiser-Meyer-Olkin measures the homogeneity of variables, and Bartlett's test of sphericity provides hypothesis testing on whether the correlation matrix is inappropriate (Eyduran et al., 2010). A Kaiser-Meyer-Olkin of greater than 0.60 is acceptable for factor analysis. This sample provided a value of 0.907, which offered sufficient evidence of the homogeneity of the variables. Bartlett's test of sphericity was significant at the $p < .001$ level ($df = 136$), which provided sufficient evidence to reject the null hypothesis that the correlation matrix was actually an identity matrix and inappropriate to use in factor analysis.

Using the maximum likelihood extraction method, all of the extraction communalities were greater than 0.3 for the initial values, with the lowest being at 0.607, indicating a strong relationship. However, one or more communality estimates were greater than during the iterations, indicating that the resulting solution should be interpreted cautiously. The total variance explained by the four-factor model is 78.853%. There were eight non-redundant residuals with absolute values greater than 0.05, which is less than 1%. As evidence of converging validity, all loadings in the pattern matrix were above 0.5 except variables that crossloaded, which helped to determine the stronger crossload as the identified factor for the matrix (see Table 4).

Table 4

Pattern Matrix From Explanatory Factor Analysis

	PU	PEU	COVID	ATT
Cronbach's alpha	0.958	0.941	0.793	0.947
I feel using an LMS would be easy for me.		0.811		
I feel my interaction with an LMS would be clear and understandable.		0.910		
I feel that it would be easy to become skillful at using an LMS.		0.857		
I would find an LMS to be flexible to interact with.		0.708		
Learning to operate an LMS would be easy for me.		0.920		
It would be easy for me to get an LMS to do what I want to do.		0.847		
Using an LMS in my job would enable me to accomplish tasks faster.	0.832			
Using an LMS would improve my job performance.	0.820			
Using an LMS in my job would increase my productivity.	1.009			
Using an LMS would enhance my effectiveness on the job.	0.905			
Using an LMS would make it easier to do my job.	0.891			
I would find an LMS useful in my job.	0.690			
I believe it is a good idea to use an LMS.	0.455			0.563
I like the idea of using an LMS.				0.715
Using an LMS is a positive idea.				0.817
The COVID shutdown helped demonstrate the usefulness of an LMS in the classroom.			0.650	
The COVID shutdowns helped demonstrate how easy an LMS was to use in the classroom.			0.777	

Note. *N* = 121; PU = perceived usefulness; PEU = perceived ease of use; COVID = effect of COVID; ATT = attitude toward use.

The discriminant validity is endorsed by the factor correlation matrix that only had one pair of values (PU and COVID) that were only slightly greater than the threshold of 0.7. This indicated that while the correlations were high, they were not so high that they demonstrated a sharing of variance as demonstrated in Table 5.

Table 5

Factor Correlation Matrix

Factor	1 (PU)	2 (PEU)	3 (COV)	4 (ATT)
1 (PU)	1.000	0.535	0.636	0.729
2 (PEU)	0.535	1.000	0.381	0.569
3 (COV)	0.636	0.381	1.000	0.502
4 (ATT)	0.729	0.569	0.502	1.000

Note. *N* = 121

Confirmatory Factor Analysis

Analysis of the sample revealed the converging validity of the model as evidenced by the average variance extracted, all of which were above 0.5 (Hair et al., 2010). Reliability was evidenced through composite reliability, all of which were above 0.7 (Hair et al., 2010). There was discriminant validity based on the square root of the average variance extracted found greater than any inter-construct correlation and the average variance extracted greater than the maximum shared variance (Malhotra & Dash, 2011). Table 6 illustrates the results of the factor analysis.

Table 6

Confirmatory Factor Analysis Validity Constructs

Variables	CR	AVE	MSV	MaxR(H)	ATT	PEU	PU	COV
ATT	0.956	0.880	0.728	0.980	0.938			
PEU	0.945	0.742	0.452	0.948	0.672	0.861		
PU	0.962	0.807	0.728	0.969	0.853	0.598	0.898	
COVID	0.824	0.701	0.626	0.825	0.739	0.570	0.791	0.837

Note. CR = Composite reliability; AVE = average variance extracted; MSV = maximum shared variance; MaxR(H) = reliability coefficient H; ATT = attitude toward use; PEU – perceived ease of use; PU = perceived usefulness; COVID = effect of COVID-19 protocols.

Next, a standard method bias test was performed for potential bias in those teaching and those not currently teaching and for a potential unknown common latent variable that was unobserved. There was a significant difference at the $p < 0.001$ level between the unconstrained model when introducing the variable of whether the faculty were currently teaching or not currently teaching and the fully constrained zero constrained model. The difference in the chi-squared values was 192.3, and the difference in the degrees of freedom was 17, which resulted in a p value less than 0.001.

There was also a significant difference at the $p < .001$ level between the unconstrained common method factor and the fully constrained common method factor. The difference in the chi-squared values was 65.1, and the difference in the degrees of freedom was 17, which resulted in a p value less than .001. When a standard method bias test was performed on both potential sources of bias, the current state of teaching, and some common latent variable, there was a significant difference between the fully unconstrained model and the fully zero constrained model at the $p < .001$ level. The difference in the chi-squared values was 65.2, and the difference in the degrees of freedom was 17, which resulted in a p value less than .000.

According to Hu and Bentler (1999), certain key thresholds serve as a guideline to determine whether the model can have a goodness of fit. The model should have a ratio of the chi-square statistic to the degrees of freedom less than three, and this model has a ratio of 138.541 to 92, which calculates to less than 1.51. The model is significant at the $p = .001$ level, so the null hypothesis that the default model is correct is rejected. The Comparative Fit Index(CFI) should be greater than 0.95, of which this model is 0.980. The Adjusted Goodness of Fit (AGFI) should be greater than 0.80, of which this model is 0.811. The Root Mean Square Error of Approximation (RMSEA) should be less than 0.10 for acceptable levels, of which this model is 0.065, which results in a p value for the closeness of fit test (PCLOSE) of $p = .136$. This value implies that the probability of getting a sample RMSEA as large as .065 is 0.136, and we fail to reject the null hypothesis that the RMSEA is greater than 0.05 or a close-fitting model.

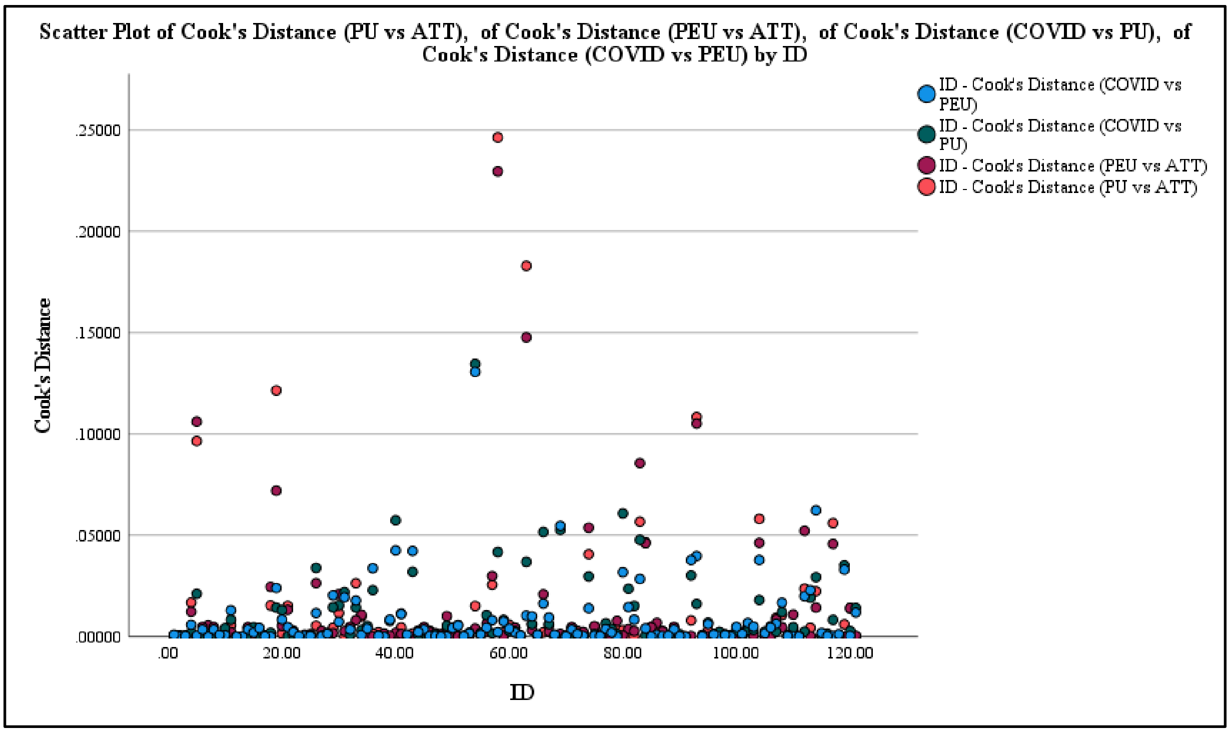
Influential Points

The next step in confirmatory factor analysis is to assess whether influential points exist in the model. Cook's distance measure was calculated for each data point and pair of independent and dependent variables based on the hypothesized model to determine influential points. According to Aguinis et al. (2013), Cook's D_i is an indicator that quantifies the influence of data points on the regression equation as a whole. Aguinis et al. (2013) also indicate a lack of consensus on precise cutoffs for which data values are overly influential but rather suggest the use of an index plot with case numbers on the x-axis and D_i values on the y-axis to be able to identify those values that are differentiated from the others visually.

The plot in Figure 4 indicates four cases with two of their four Cook's Distance values greater than .10000 and three of them that were visually different from other points like them. This excludes cases 58, 63, and 54 because of their potential influential status. To verify this conclusion, comparing the coefficient of determination for each of the calculated linear regressions from before and after the removal of the cases is recommended. However, when comparing these coefficients of determination, the values went lower for each regression line, and thus the decision was made to include these samples despite their potential influential behavior.

Figure 4

Scatter Plot for Determining Potential Influential Points



Multicollinearity

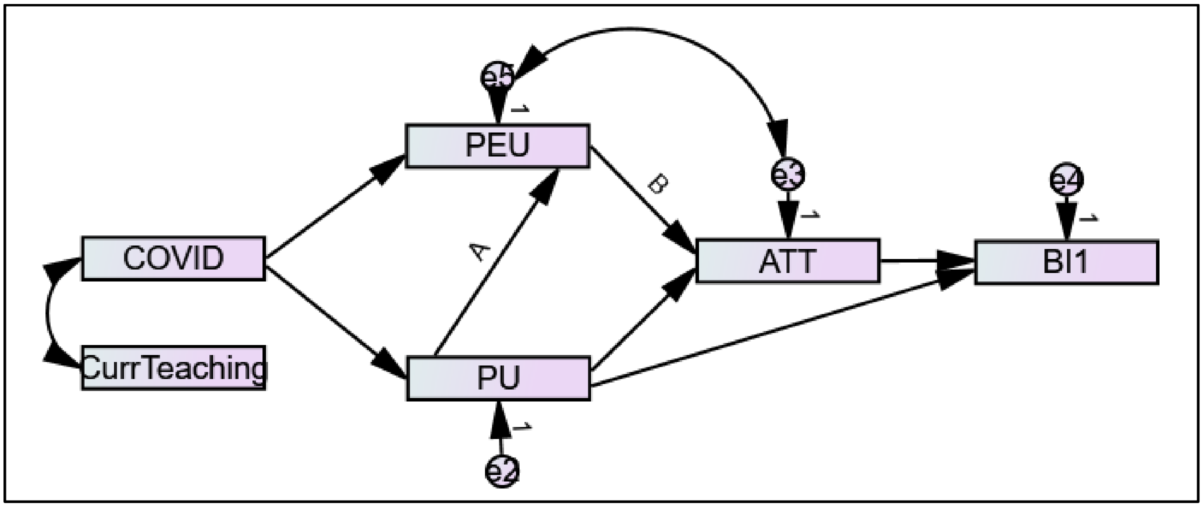
Multicollinearity violates one of the conditions of using structural equation modeling when there is an approximately linear relationship among the independent variables (Liu et al., 2003). Multicollinearity is highly probable when the collinearity statistics of tolerance and variance inflation factor (VIF) are beyond their traditional scopes. When the VIF is beyond 10, there is a high probability that the linear relationships are interrelated and potentially redundant. In this instance, VIF for PU is 19.269 and 29.607 for PEU. The high values for VIF suggest a high probability of multicollinearity, which in this instance is not altogether a problem in that it fits the hypothesized model because, in the hypothesized model, the response to the COVID variable is a predictor of both PEU and PU, which implies they may be collinear responses to the same stimuli.

Mediating Relationships

Previous research, such as conducted by Mohammadi (2015), indicated that PU sometimes mediated the relationship between PEU and ATT, especially when ease of use drove the first use of the technology. In this instance, PEU seems to be the mediating factor between PU and ATT, as higher education faculty were asked to use LMS to be able to interact with remote students and then sometimes found that the ease of use of their learning management system changed their attitude regarding the use of an LMS. This relationship was tested using the AMOS AxB Estimand tool (Gaskin, 2022) to examine the mediation effect as conventional methods recommended by researchers (Baron & Kenny, 1986; Dissanayake, 2018) when multiple pathways exist between independent and dependent variables, as displayed in Figure 5. The relationship of PEU was found to be a mediating relationship between PU and ATT and was significant at the $p = .049$ level. The estimate of the mediating relationship is 0.256, with a standard error of 0.166.

Figure 5

The Mediating Relationship of PEU AxB Estimand Tool



Interactions Moderation

The next step was a method for exploring moderating interactions. A moderating interaction is any variable that impacts the direction or strength of the relation between an independent variable and a dependent variable (Baron & Kenny, 1986). Three potential variables were explored with the potential of different levels of experience that could impact the PU or PEU when accounting for the perceptions of the COVID shutdowns.

The survey questions measuring experience with a learning management system (LMSExp), experience at the faculty member's current institution of higher learning (CurrFacExp), and the faculty member's cumulative experience in higher education were analyzed. Cumulative experience demonstrated no significant impact on the model; however, the other two variables did provoke further exploration as they generated large enough critical ratios such that the slope was statistically significantly different than zero at the $\alpha = 0.10$ level.

LMSExp dampens the positive relationship between COVID and PEU, and both regression weights were significant at $\alpha = 0.05$ level. LMSExp dampens the positive relationship between COVID and PU, and both regression weights were significant at the $\alpha = 0.05$ level. This implies that when the experience with an LMS is high, there was a negative relationship between the value of the effect of COVID and both PEU and PU. Similarly, when the experience with an LMS is low, there was a positive relationship between the value of the effect of COVID and both PEU and PU.

These statements make logical sense as to the situation in that if a faculty member already had high experience with an LMS, COVID had little effect on their perceptions relative to other faculty that had little experience with an LMS and thus had strong changes in their perceptions of LMS. However, the model has no effect of LMSExp on PU, so LMSExp is only included as a moderating factor on PEU.

CurrFacExp strengthens the positive relationship between COVID and PEU, although not at an $\alpha = 0.05$ significance level. CurrFacExp strengthens the positive relationship between COVID and PU, and both regression weights were significant at $\alpha = 0.05$ level, but there is no effect on the estimation of PU, so CurrFacExp was not included as an interaction factor.

Multigroup Analysis

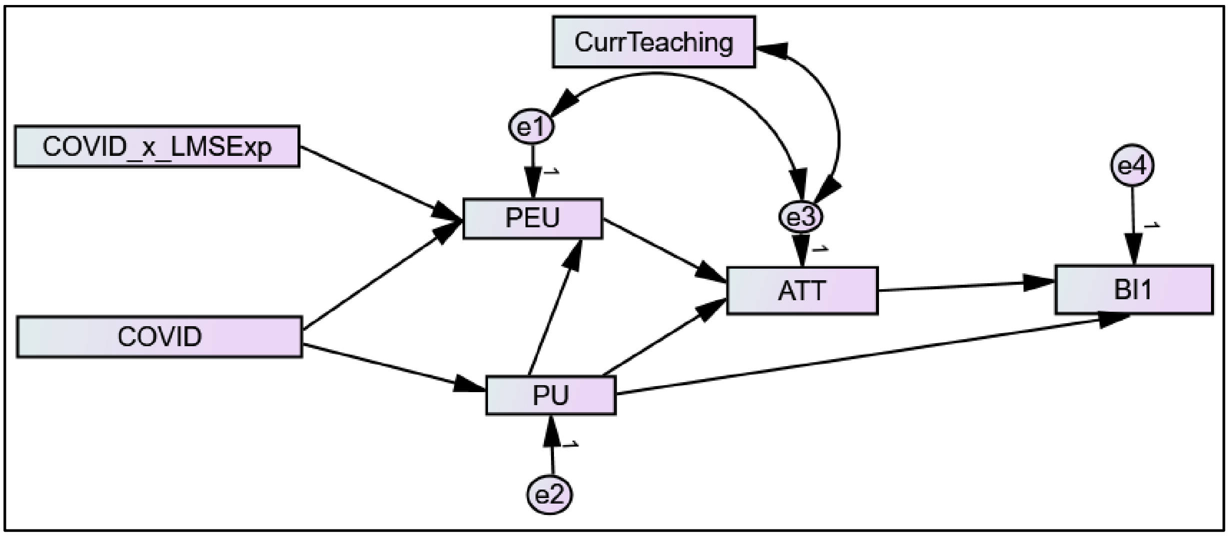
Multigroup analysis was performed on the potential bias source measured earlier in whether faculty currently teaching have a different response than those not currently teaching. The multigroup analysis tool in AMOS demonstrated that the groups were significantly different at the $p = .047$ level using a chi-squared test for differences in the structural weights of the regression lines. The tool also revealed that the differences occurred on the two regression lines that affect the formation of the attitude toward the intent to use LMS. The PU to ATT regression line was significantly different at the $p = .048$ level with 4 degrees of freedom, and the PEU to ATT regression line was significantly different at the $p = .035$ level with 4 degrees of freedom.

Final Model

The results of the confirmatory factor analysis indicated that each item loaded on its respective underlying concept and all loadings were significant for each of the four observed endogenous variables of BI1, PU, ATT, and PEU and the three observed exogenous variables of COVID, CurrTeaching, and COVID_x_LMSExp as demonstrated in Figure 6.

Figure 6

TAM Regarding the Use of LMS by Faculty Post-COVID



Construct reliabilities were also assessed for every construct. To view the complete list of items, loadings, and critical ratios (see Table 7). The model fit indices also suggest that the measurement model was a good fit to the data (comparative fit index [CFI] = 0.995, goodness of fit index [GFI] = 0.962, root mean square error of approximation [RMSEA] = 0.050, *p* value for closeness of fit [PCLOSE] = 0.459). Under the hypothesis of "close fit" (i.e., that RMSEA is no greater than 0.05 in the population), the probability of getting a sample RMSEA as large as 0.050 was 0.459.

Table 7

Confirmatory Factor and Reliability Analysis

Constructs	Regression weights	Critical ratio
Perceived Effect of COVID Protocols on use of an LMS		*6.536*
The COVID shutdown helped demonstrate the usefulness of an LMS.	.824	**
The COVID shutdown helped demonstrate how easy an LMS was to use.	.852	9.651
PEU of an LMS		*6.696*
I feel using an LMS would be easy for me.	.811	**
I feel my interaction with an LMS would be clear and understandable.	.910	16.641
I feel it would be easy to become skillful at using an LMS.	.857	11.714
I would find an LMS to be flexible to interact with.	.708	13.418
Learning to operate an LMS would be easy for me.	.909	12.054
It would be easy for me to get an LMS to do what I want to do.	.847	12.131
PU of an LMS		*6.223*
Using an LMS in my job would enable me to accomplish tasks faster.	.832	**
Using an LMS would improve my job performance.	.820	15.715
Using an LMS in my job would increase my productivity.	1.009	16.493
Using an LMS would enhance my effectiveness on the job.	.905	14.576
Using an LMS would make it easier to do my job.	.891	15.597
I would find an LMS useful in my job.	.691	11.471
ATT of an LMS		*6.295*
I believe it is a good idea to use an LMS.	.562	**
I like the idea of using an LMS.	.714	16.376
Using an LMS is a positive idea.	.817	16.831

Note. N = 121; italicized values are the critical ratios for variables; all variables were significant at the p = < .001 level.

Findings for Research Question 1

To answer RQ1 on the effect of COVID-19 protocols on the PEU of LMS, the model developed using AMOS and SPSS from the survey research tool was utilized to provide supporting evidence.

The squared multiple correlation of PEU is 0.966. It is estimated that the predictors of PEU explain 96.6% of its variance. In other words, the error variance of PEU was approximately 3.4 %t of the variance of PEU itself. This value indicates a very strong positive linear relationship. This prediction model was based on the calculated COVID and PU variables with a moderating effect of LMSExp.

The estimate of the slope directly between the independent variable COVID and the dependent variable PEU was 0.253 with a standard error of 0.025, or for every value on the Likert scale that the variable of COVID rises, the variable of PEU rises by 0.253.

The standardized indirect (mediated) effect of COVID on PEU was 0.587. That is, due to the indirect (mediated) effect of COVID on PEU, when COVID increased by one standard deviation, PEU increased by 0.587 standard deviations.

The total (direct and indirect) effect of COVID on PEU was 0.787. That is, due to both direct (unmediated) and indirect (mediated) effects of COVID on PEU, when COVID increased by 1, PEU increased by 0.787.

The positive correlation and mediating factors that increase the indirect effect of COVID on PEU imply that COVID-19 protocols did indeed have a powerful impact on higher education faculty's perception of the ease of use of LMS.

Findings for Research Question 2

To answer RQ2 on the effect of COVID-19 protocols on the PU of LMS, the model developed using AMOS and SPSS from the survey research tool was utilized to provide supporting evidence.

The squared multiple correlation was 0.619. It is estimated that the predictors of PU explain 61.9% of its variance. In other words, the error variance of PU is approximately 38.1% of the variance of PU itself. This value is an indication of a strong positive linear relationship. This prediction model was based on the calculated COVID variable with a moderating effect of LMSExp.

The standardized direct (unmediated) effect of COVID on PU was 0.784. That is, due to the direct (unmediated) effect of COVID on PU, when COVID increased by one standard deviation, PU increased by 0.784 standard deviations. This direct effect is in addition to any indirect (mediated) effect that COVID may have on PU.

Findings for Research Question 3

To answer RQ3 on the perceptions of higher education faculty regarding the behavioral intent to use LMS during COVID-19, statistical analysis of the variable behavioral intent and assessment of the model developed using SPSS and AMOS was utilized to provide supporting evidence.

The median and mode of the statement, "I plan to use/continue to use an LMS in the future" was a seven (strongly agree) on a Likert scale of 1–7. Eighty-six percent of faculty surveyed strongly agreed with the statement, with only one survey participant on the disagree side of that statement. This distribution was strongly skewed towards the smaller values with a measure of skewness of -4.438.

The model generated a squared multiple correlation of 0.309. It is estimated that the predictors of BI explain 30.9% of its variance. In other words, the error variance of BI is approximately 69.1% of the variance of BI itself. This value is an indication of a moderate positive correlation.

The standardized total (direct and indirect) effect of COVID on BI1 is 0.422. That is, due to both direct (unmediated) and indirect (mediated) effects of COVID on BI1, when COVID increases by one standard deviation, BI1 increases by 0.422 standard deviations. Overall, higher education faculty have a high likelihood of using LMS in the future, and COVID appears to have influenced that behavior based on the correlation and effect on behavioral intent from COVID protocols.

Findings for Research Question 4

To answer RQ4 regarding a change in higher education faculty's perceived acceptance of LMS due to COVID-19, a model was developed using the AMOS and SPSS survey research tools to provide supporting evidence. The model-implied correlation between COVID and ATT was 0.758. This correlation suggests a strong positive linear relationship exists between faculty's perceptions of the effect of COVID protocols and their ATT of an LMS.

The standardized total (direct and indirect) effect of COVID on ATT was 0.758. That is, due to both direct (unmediated) and indirect (mediated) effects of COVID on ATT, when COVID increased by one standard deviation, ATT increased by 0.758 standard deviations. The standardized total (direct and indirect) effect of COVID on BI1 was 0.422. That is, due to both direct (unmediated) and indirect (mediated) effects of COVID on BI1, when COVID increased by one standard deviation, BI1 increased by 0.422 standard deviations.

Because of the positive linear relationship implied by the model, COVID-19 has likely influenced higher education faculty's perceptions of LMS and led toward a likely acceptance of LMS by a broader population of faculty.

Chapter 5: Discussion, Conclusions, and Recommendations

This study examined higher education faculty's perceptions of LMS due to a potential DX during the COVID-19 global pandemic. This chapter discusses significant findings related to the literature on the use of LMS in higher education, the impact of COVID-19 on learning in higher education, DXs, and the TAM. Also included is a discussion on connections to this study, leadership in educational technology, and adoption of educational technology tools. The chapter concludes with a discussion of the study's limitations, recommendations for future research, and a brief summary.

This chapter contains discussion and future research possibilities to help answer the research questions:

RQ1: What is the effect of COVID-19 protocols on the perceived ease of use of LMS in higher education?

RQ2: What is the effect of COVID-19 protocols on the perceived usefulness of LMS in higher education?

RQ3: What are the perceptions of higher education faculty regarding the behavioral intent to use LMS during COVID-19?

RQ4: Has perceived acceptance of learning management systems changed for higher education faculty since COVID-19?

Discussion of Findings in Relation to Past Literature

While personal reasons for the intent to use LMS in the future may vary, the generalized model suggested by the research study demonstrated that COVID-19 plays a part in a faculty member's acceptance of LMS. The need to interact with students during remote or socially distanced learning environments demonstrated the PU of the technology. As faculty members attempted to use their campus's LMS, the PEU increased, leading to a positive ATT and a BI to use LMS in the future.

Impact of COVID-19 Protocols on DX and BI in Higher Education

This study's conclusion that higher education faculty have a high BI to use LMS due to their experiences of teaching during implementation of COVID-19 protocols is further evidence of the DX occurring in higher education. According to Vial (2019), DXs occur when technologies impact the behavior of consumers to the point where previous solutions are no longer seen as viable options. During COVID-19, faculty witnessed the potential for remote interaction with students, the ever-widening availability of digital tools in LMS, and the relative ease of use of most LMS. Because of these benefits and increased support from administrators, faculty reported their positive ATT and have transitioned through the final steps of the DX surrounding the use of LMS as a primary communication piece in higher education.

According to Leoste et al. (2021), while most institutions had elements of the infrastructure necessary to provide access to online learning environments, many students and faculty struggled with the personal home infrastructure or online learning skills necessary during the quick transition to a completely online environment. Johnson et al. (2020) stated that this was not an online learning environment but a hurried approach to remote education, especially for those who lacked experience in online pedagogical strategies. Because of this remote teaching experience, faculty attempted new teaching methodologies and assessments and began exploring online pedagogical skills while using their LMS. According to Tick and Beke (2021), even institutions or faculty at the early stages of adopting LMS were forced to increase their involvement and revise their delivery modes and pedagogical methods.

Impact on the TAM

The TAM was developed in 1989 by Fred Davis to develop and validate constructs that would help explain computer usage (1989). Since then, it has been the theoretical framework of numerous research studies and has been used to describe the acceptance of different technologies (Marangunić & Granić, 2014). Other research has sought to improve the model by using new observed variables to help improve the prediction power of the model (Binyamin et al., 2019).

COVID-19 impacted the perceptions of LMS with higher education faculty in the four constructs modeled in the TAM. The measurements of PEU, PU, ATT, and BI to use LMS each had a measured effect on the faculty member's experiences with teaching during COVID-19 protocols put in place by institutions of higher education. These factors led to a high intent to use learning management in the future and the faculty's perceived acceptance of LMS.

This research sought to demonstrate that an external event has the potential to affect a user's acceptance of technology. The COVID-19 global pandemic forced higher education faculty to find technological solutions to instruct students remotely or to engage students while socially distancing. While many faculty were proficient users of their school's LMS, others had only used it with minimal functionality, and others were not using it for various reasons. This research demonstrated a strong positive linear relationship ($r^2 = 0.743$) between the perceived effect of COVID-19 protocols and higher education faculty's ATT towards LMS, with a slope of 0.758 standardized units between the two variables. These values imply that the perception of COVID-19 protocols explains 74.3% of the variance in the model and strongly predicts the positive linear relationship.

Impact on PEU

Because faculty were asked to use their institution's learning management system for a prolonged period in the instruction of students during the COVID-19 shutdowns and following social distancing instruction, faculty were able to internalize the usefulness of the software and realize that the technology was not as challenging to use as previously perceived. These findings demonstrate that large-scale events and not just individual constructs can influence the acceptance and behavioral intent of technologies given a strong enough influence. Educational technology leaders can thus capitalize on the acceptance of LMS in their institutions and utilize this acceptance to push forward quality instructional design principles in the online classroom.

Impact on Higher Education Technology Leaders

Educational technology leaders can now push for even late adopters and laggards of technology innovation to accept the universal use of LMS. In this research, 86% of participants strongly agreed that they would likely use an LMS in the future. Another 12.4% of participants were on the agree side of the seven-point Likert scale. This overwhelming majority of 98.4% of higher education faculty provides a tipping point in the use of LMS. This statistic provides evidence that faculty who do not intend to use LMS are now the exception and not in a normative group which helps provide an incentive for these exceptions to adopt LMS for the benefit of their students.

Impact on PU as a Primary Engagement Tool

An additional benefit of this research was a change in the mediating factor from previous models. Previously PU was a mediating factor between PEU and ATT. In this model, PEU became the mediating factor between PU and ATT. This finding means that in the past, a proportion of the users saw the ease of use before they saw the usefulness of the technology and then had a change in attitude. In this model, a proportion of the potential LMS users first saw the usefulness of the technology and then the ease of use of LMS before adopting their attitude. This change in the mediating factor is potentially dramatic in how technology is presented to faculty for acceptance. This is a potential transition to fully demonstrate the potential usefulness of technology to increase adoption in contrast to demonstrating how simple the technology is to use. This change may be limited to the extended effect of COVID-19 protocols and is worthy of further research on future technologies.

Other Potential Impacts

An additional finding of this research is the slightly negative covariance, although not statistically significant at the $\alpha = 0.05$ level, between whether faculty were currently teaching and their ATT of a LMS. Of those surveyed, 9.9% responded that they were not currently teaching. The first model produced a covariance between currently teaching and the perceptions of COVID-19 protocols. The result showed that the relationship was more robust with their ATT of LMS, and those who were not teaching had a lower average ATT than those who were teaching. This might imply the potential of future bias, the resistance to change to a new normal with the use of technology, and the potential of extended change in educational technology expectations.

A final finding in this model was that as faculty had increased experience with LMS, this imposed a weak but statistically significant ($\alpha = 0.05$) negative moderating effect on the impact of COVID-19 protocols on PEU but not PU. This finding implies that faculty with increasing experience in LMS had little to no problems adapting to the use of LMS during COVID-19 shutdowns but saw a strengthening of their perception of the usefulness of LMS. For faculty experienced in LMS, the increased global use of LMS was an extension of practices they had already put into place and had less effect on their daily online teaching practices than those with less experience.

Limitations

The factors beyond the researcher's control and potentially impacting the research outcome are known as limitations (Roberts & Hyatt, 2019). A potential limitation of the study is that participants who respond to the survey may have intense emotions regarding the use of LMS in higher education ,COVID-19 conditions, or teaching during government-imposed shutdowns; thus, they may be overrepresented in the sample. By self-selecting to respond to the survey, those participants may be overrepresented from the actual population, and the use of a web survey confounds this potential by its ease of selection or rejection by the participant (Castro-Martin et al., 2021). A limitation of web surveys is that it automatically selects a subset of the population of those who use the internet or, even more specifically, where an element of the group is contacted to participate in the survey (Castro-Martin et al., 2021). The use of self-reported perceptions from participants also can overrepresent actual attitudes and intentions that are an element of this model (Sundström, 2011). A further limitation is the honest responses of the participants and their understanding of the questions concerning their experiences.

Other limitations of this study involve the timing of the survey. Because this study gathers baseline data, it cannot be compared to the prior perceptions nor can it currently provide data on whether intent to use will translate to actual usage.

The converse of limitations, known as delimitations, focus on factors that could potentially impact the outcome of the research over which the researcher did have a modicum of control (Roberts & Hyatt, 2019). A delimitation of the methodology used to measure findings in this research was the use of self-reported information of perceptions. One of the potential delimitations of the study is that the study is only designed to observe one form of technology adopted during COVID-19, and the findings of this research are not necessarily generalizable to all technologies adopted during the periods of shutdown. Another delimitation is that while other hypothetical models might have potentially fit the scenario better, the TAM was the model chosen as the subject of research. A final delimitation is using a convenience sample from social media groups and listservs to achieve a large enough sample size, potentially limiting the research's generalizability.

Recommendations for Future Research

Several implications from this research study arise and provide potential opportunities for future research. This observational study was limited to the faculty's perceived acceptance of LMS during COVID-19. While the findings of this study contribute to the existing body of research, there remain many areas to investigate regarding faculty perceptions of LMS usage. Future studies are recommended that expand the population studied to include faculty from different levels of education, including elementary and secondary schools. Future research might also include whether different levels of education, even within higher education, responded differently to the TAM constructs. Future research might also include investigating the influence of different brands of LMS, especially on PEU and usefulness.

Future research should also follow through on whether faculty follow through on their BI to use an LMS and use them over the long term. Future research should also investigate the relationship between the diffusion of innovations theory by Rogers (2003) and whether a technology user's general position on the diffusion of innovation curve influences TAM's perceived constructs.

Further research should also be done on whether the mediating factor of PEU will remain an element of the model or if this is because of the impact of COVID-19 and the need to find a useful solution to remote teaching. Further research should also center on the design of professional development tailored to impact ATT concerning adopting LMS. Further research should also be conducted with students to see if the COVID-19 construct was also a strong indicator of acceptance of LMS.

Conclusions

Institutions of higher education continue to invest in a technology designed for teaching and learning and expect to see a return on those investments in the form of data demonstrating impactful practices and usage of the technology for the intended and innovative pedagogical practices. As educational technology leaders, the ability to understand constructs that influence the attitudes surrounding adopting LMS and how remote teaching during COVID-19 and the transition to online learning has impacted faculty in higher education.

Understanding that COVID-19 has impacted faculty's intent to use LMS at a global level provides new and exciting opportunities in the field of educational technology. Educational technology leaders can now provide resources that strengthen the resolve to use the technology tools that have a measured impact on teaching and learning practices and the ability to facilitate the achievement and measurement of learning outcomes. Providing resources that demonstrate the usefulness and then the ease of use of a learning management system will help in the overall acceptance as faculty become expert users of the technology.

Over time as new technology tools need to be adopted to address a crisis or severe deficit in nontechnical solutions, this research has the potential to lay a foundation for those plans to implement interventions to provide faculty with research-based interventions.

Davis (1993) claimed that "Lack of user acceptance has long been an impediment to the success of new information systems" (p. 475). By extending the TAM to include variables that are indicative of time and circumstance rather than just perceptions and cognitive or emotional constructs, this research acknowledges that extenuating circumstances have the potential to influence the acceptance of technology.

In conclusion, higher education institutions should develop strategic plans and provide professional development resources that help increase the acceptance of the institution's learning management system that include the constructs of PU and PEU, especially during these years immediately following the global recovery from COVID-19. The results of this study could also provide insight into future selections or enhancements regarding LMS as institutions consider their current investment in teaching and learning with technology.

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Appendix A: Solicitation Email

Hello, my name is Stephen Rektenwald, and I am a doctoral student at Abilene Christian University. I am doing a research study entitled The Acceptance of Learning Management Systems by Higher Education Faculty in an Educational Landscape Influenced by a Global Pandemic in partial fulfillment of the requirements for my degree. The purpose of the study is to identify whether higher education faculty's acceptance of learning management systems was influenced by their use of them during the recent COVID-19 shutdowns and distance learning protocols. To qualify to participate, you must be a higher education faculty member who explored or used learning management systems during the last two years

Participation would require less than 4 minutes of your time, to complete an anonymous survey.

If you are interested in participating, please *use this link* and you will be presented a consent form in the survey to understand more information regarding this study. If you would like to receive more information upon completion of this study or have any questions about the study, feel free to contact me at xxxxxxxxxxxxxxxxx@acu.edu and I will help you out in any way that I can.

Sincerely,

Stephen Rektenwald

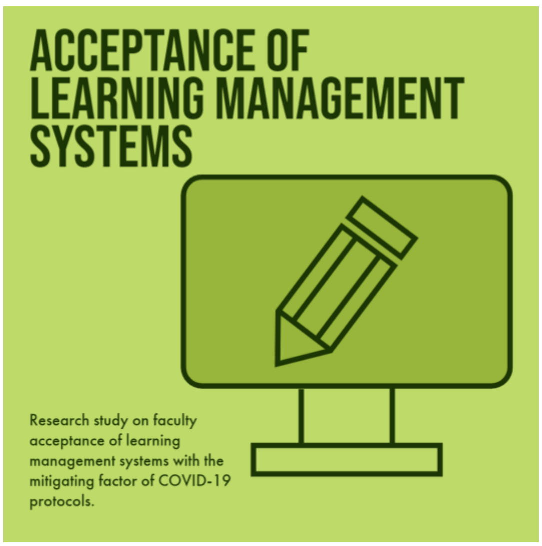
Appendix B: Solicitation Post to Facebook Groups

Hello, my name is Stephen Rektenwald, and I am a doctoral student at Abilene Christian University. I am doing a research study entitled The Acceptance of Learning Management Systems by Higher Education Faculty in an Educational Landscape Influenced by a Global Pandemic in partial fulfillment of the requirements for my degree. The study aims to identify whether higher education faculty's acceptance of learning management systems was influenced by their use of them during the recent COVID-19 shutdowns and distance learning protocols. To qualify to participate, you must be a higher education faculty member who explored or used learning management systems during the last two years.

Participation would require less than 4 minutes of your time to complete an anonymous survey. If you are interested in participating, please use this link, and you will be presented with a consent form via the survey to understand more information regarding this study. If you would like to receive more information upon completion of this study or have any questions about the study, please contact me at xxxxxxxxxxxxx@acu.edu, and I will help you out in any way that I can.

Sincerely,

Stephen Rektenwald



Appendix C: Survey Questionnaire

We are interested in understanding the mitigating factor of the COVID pandemic on the acceptance of learning management systems in higher education by faculty. Learning Management Systems as defined in this research are self-contained websites that allow faculty to conduct teaching and learning activities such as but not limited to discussion boards, distribution and collection of assignments, gradebooks, delivery of media content, and distribution of class materials such as syllabi.

You will be presented with information relevant to this study and asked to answer some questions about it. Please be assured that your responses are anonymous and will be kept completely confidential.

The study should take you around 6 minutes to complete. Your participation in this research is voluntary. You have the right to withdraw at any point during the study, for any reason, and without any prejudice. If you would like to contact the Principal Investigator in the study to discuss this research, please e-mail xxxxxxxxxxxx@acu.edu

By clicking the button below, you acknowledge that your participation in the study is voluntary, you are at least 18 years of age, and that you are aware that you may choose to terminate your participation in the study at any time and for any reason.

Please note that this survey will be best displayed on a laptop or desktop computer. Some features may be less compatible for use on a mobile device.

I consent, begin the study
I do not consentI do not wish to participate.

Demographics

Over the last two years, I have used or have investigated the possibility of using an LMS for instruction in higher education.

Yes
No

Current Academic Rank

Professor
Associate Professor
Assistant Professor
Lecturer
Instructor
Adjunct Faculty
Other

How do you describe yourself?

Male
Female
Non-binary / third gender
Prefer to self-describe
Prefer not to say

Faculty experience in higher education (cumulative)

Less than 1 year
At least 1 year and less than 3 years
At least 3 years and less than 5 years
At least 5 years and less than 10 years
At least 10 years

Are you currently teaching?

Yes
No

If no, when did you stop teaching?

Less than 1 year
Less than 2 years
More than 2 years ago

Faculty experience in higher education at current institution

Less than 1 year
At least 1 year and less than 3 years
At least 3 years and less than 5 years
At least 5 years and less than 10 years
At least 10 years

How long have you used a Learning Management System for teaching and learning?

Less than 1 year
At least 1 year and less than 3 years
At least 3 years and less than 5 years
At least 5 years
Have not used a Learning Management System

Which Learning Management System (LMS) is your institution currently using?

Absorb LMS
Blackboard
Canvas by Instructure
CertCentral
D2L Brightspace
Edmodo LMS
Google Classroom
LearnDash
Moodle
Schoology
Other
Do Not Know

LMS Usage Constructs

Rate your level of agreement with each statement (1 = Strongly Disagree to 7 = Strongly Agree).

	1	2	3	4	5	6	7
I feel that using an LMS would be easy for me.							
I feel that my interaction with an LMS would be clear and understandable.							
I feel that it would be easy to become skillful at using an LMS.							
I would find an LMS to be flexible to interact with.							
Learning to operate an LMS would be easy for me.							
It would be easy for me to get an LMS to do what I want to do.							
I feel that my ability to determine LMS ease of use is limited by my lack of experience.							
Using an LMS in my job would enable me to accomplish tasks more quickly.							
Using an LMS would improve my job performance.							
Using an LMS in my job would increase my productivity.							
Using an LMS would enhance my effectiveness on the job.							
Using an LMS would make it easier to do my job.							
I would find an LMS useful in my job.							
I feel that my ability to determine the usefulness of my LMS is limited by my lack of experience.							
I believe it is a good idea to use an LMS.							
I like the idea of using an LMS.							
Using an LMS is a positive idea.							
I plan to use or continue to use an LMS in the future.							

	1	2	3	4	5	6	7
Probably, I will use an LMS in my daily instruction.							
Before the COVID lockdowns, I was already a proficient LMS user.							
The COVID lockdowns helped to demonstrate the usefulness of an LMS in the classroom.							
The COVID lockdowns helped to demonstrate how easy an LMS was to use in the classroom.							

Appendix D: Permission to Use a Modified Version of the TAM Survey

Stephen Rektenwald <xxxxxx@acu.edu> Tue, Mar 8, 2022 at 9:08 PM
To: xxxxxxxxxx@utas.edu.au

Hello Dr. Drew,

My name is Stephen Rektenwald, and I am currently pursuing my EdD in Organizational Leadership with an emphasis in learning with emerging technologies at Abilene Christian University. The tentative topic of my research study is The Acceptance of Learning Management Systems by Higher Education Faculty in an Educational Landscape Influenced by a Global Pandemic. Based on a review of the literature, I believe there may be a relationship between the acceptance of learning management systems and the environment that faculty were forced to teach in during the COVID-19 pandemic. I am writing in hopes that you might grant me permission to modify and administer the version of the technology acceptance model that you and Dr. Alharbi wrote about in your 2014 article Using the Technology Acceptance Model in Understanding Academics' Behavioural Intention to Use Learning Management Systems. I will be modifying the survey with an element of the inclusion of the influence of COVID-19 teaching conditions as a modifying factor and demographics for higher education faculty. I will be sure to provide the appropriate citation and acknowledgment. Thank you for the work you are doing in this area of study. I look forward to your response.

Sincerely,

Stephen Rektenwald, M.Ed.
Assistant Director of Innovation Foundry and Educational Technology

Steve Drew <xxxxxxxxxx@utas.edu.au> Tue, Mar 8, 2022 at 9:25 PM
To: Stephen Rektenwald <xxxxxx@acu.edu>

Dear Stephen,

Thank you for asking. Please feel free to build upon any aspect of this work. I believe that COVID-19 will be an interesting modifier. It would also be interesting to see how that potential modifier changes over time, as the post-COVID world adapts.

Good luck with your studies!

Warm regards
Steve

Steve Drew PhD MHEd **ORCiD: 0000-0002-8601-9815**
Senior Lecturer - Professional Learning and Networks for Teachers
Tasmanian Institute of Learning and Teaching | Academic Division
University of Tasmania
Private Bag xxx Hobart TAS 7001
T +xxxxxxxx | M +xxxxxxxx

Stephen Rektenwald <xxxxxx@acu.edu> Wed, Mar 9, 2022 at 8:28 AM

To: xxxxxxxxxxx@ttu.edu

Hello Dr. Davis,

My name is Stephen Rektenwald, and I am currently pursuing my EdD in Organizational Leadership with an emphasis in learning with emerging technologies at Abilene Christian University. The tentative topic of my research study is The Acceptance of Learning Management Systems by Higher Education Faculty in an Educational Landscape Influenced by a Global Pandemic. Based on a review of the literature, I believe there may be a relationship between the acceptance of learning management systems and the environment that faculty were forced to teach in during the COVID-19 pandemic. I am writing in hopes that you might grant me permission to modify and administer a version of the technology acceptance model that you pioneered in your dissertation. I will be modifying the survey with an element of the inclusion of the influence of COVID-19 teaching conditions as a modifying factor and demographics for higher education faculty. I will be sure to provide the appropriate citation and acknowledgment. Thank you for the work you are doing in this area of study. I look forward to your response.

Stephen Rektenwald, M.Ed.
Assistant Director of Innovation Foundry and Educational Technology

Wed, Mar 9, 2022 at 8:09 PM

Davis, Fred
To: Stephen Rektenwald <xxxxxx@acu.edu>

You have my permission to modify and use the Technology Acceptance Model for your dissertation.

Best wishes

Fred Davis.

Appendix E: IRB Approval Letter

ABILENE CHRISTIAN UNIVERSITY

Educating Students for Christian Service and Leadership Throughout the World

Office of Research and Sponsored Programs
320 Hardin Administration Building, ACU Box 29103, Abilene, Texas 79699-9103
325-674-2885

May 2, 2022

Stephen Rektenwald
Department of Graduate and Professional Studies
Abilene Christian University

Dear Stephen,

On behalf of the Institutional Review Board, I am pleased to inform you that your project titled "The Acceptance of Learning Management Systems by Higher Education Faculty in an Educational Landscape Influenced by a Global Pandemic",

(IRB# 22-055)is exempt from review under Federal Policy for the Protection of Human Subjects.

If at any time the details of this project change, please resubmit to the IRB so the committee can determine whether or not the exempt status is still applicable.

I wish you well with your work.

Sincerely,

Megan Roth

Megan Roth, Ph.D.
Director of Research and Sponsored Programs

Our Promise: ACU is a vibrant, innovative, Christ-centered community that engages students in authentic spiritual and intellectual growth, equipping them to make a real difference in the world.