Technology Leadership Influence on Intention to Use AI-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs)

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Dedication

I dedicate this work to the professionals and enthusiasts of artificial intelligence (AI) and higher education (HE) globally. Thank you for sharing your thoughts during personal conversations and updates and critical analysis via professional social networks and newsletters. It stimulated me throughout the PhD program and during the dissertation writing stage.

Also, I would like to extend this dedication to the future researchers and practitioners in the field of AI and HE. The findings of this study, while make a significant first step, show the need for continued exploration and development in the field. The emerging model for intention to adopt AI tools in higher education institutions (HEIs), particularly in its early adoption phase, and the role of technology leadership in facilitating intention and use of technology in HEIs, open new pathways for research and practice. Your efforts in building upon this foundation, through further theory and methodology development, will be crucial in shaping how AI tools are understood, adopted, and utilized in educational contexts. May this work inspire and guide you in your endeavors to enhance higher education and leadership in the age of artificial intelligence.

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While my acknowledgments end here, I want to express my sincere appreciation to everyone who played a part during my PhD journey. Over the last four years, more than 100 individuals have given me valuable lessons on self-reflection, gratitude, agility, respect, and diplomacy. I have polished and elevated these skills to a higher level of proficiency during my studies at JMU. Thank you all for your contributions!

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Abstract

The purpose of this study was to test quantitatively the potential influence of Technology Leadership (TL) in Higher Education (HE) and Technophobia on Intention to Use AI-based Early Alert Systems (EAS) at higher education institutions (HEIs) by faculty and administrative staff. This research was conducted collecting and analyzing data from a mid-size higher education institution (HEI) in southeast of the Unites States. The measurement instrument used previously validated measures of Technophobia, TL in HE and Intention to Use Technology. From statistically significant findings, though of weak strength, the results showed that an individual's role in HEI (faculty vs. administrative staff), modestly but significantly positively correlates with all five sub-scales of TL in HE. Contrary, the level of terminal degree obtained showed a negative, yet also weak, statistically significant relationship with the TL in HE sub-scales. The findings also suggest that exists a potential difference in how individuals with STEM degrees and those with non-STEM degrees might differently perceive the intention to use AI tool of EAS at HEIs. However, the relationship was also weak. The practical finding of this study is the positive statistically significant effect of Empowering Leadership sub-scale of TL in HE suggesting that leaders who foster empowerment within their teams are likely to see a higher intention to use AI tool of EAS at HEIs. This study contribution was an attempt to develop a model tailoring to AI tools still in their early adoption phase, where many potential adopters may not know about its essence and functionalities. This task appeared to be challenging and requires further theory and methodology building in future research.
Keywords: artificial intelligence, higher education, technology adoption, early alert systems, technology leadership

CHAPTER 1

Introduction

Study Background

In 2019, UNESCO released the "Beijing Consensus on AI and Education," encouraging countries to formulate innovative AI educational policies, strategies and practices (UNESCO, 2019; Yang & Bai, 2020). Since then, numerous countries have been examining ways to utilize AI's potential in education, aiming to increase opportunities and minimize technology-related risks (OECD, 2023).

In 2022, the public introduction of OpenAI's generative AI tool, ChatGPT, drew global attention of media and academia, amplifying challenges for higher education institutions (HEIs) worldwide (University of Toronto, 2023). OpenAI's CEO, Sam Altman, stated that its impact would exceed the agricultural, industrial, and internet revolutions combined. ChatGPT 3.5 release signaled to the opponents of AI that we have entered the era of advanced AI with significant implications for diverse sectors, including higher education.

In recent decades, AI tools have gradually been integrated into higher education (HE). Their widespread adoption across various HEIs' functions, including admissions, research, university operations, evolving instructional and administrative jobs, is expected to change the landscape of the higher education (Chronicle of Higher Education, 2023). Moreover, the global management consulting organization's McKinsey & Company report "The economic potential of generative AI: The next productivity frontier" released in June 2023 highlights that generative AI will most impact the operations, marketing and sales functions within the educational sector, i.e., administrative tasks, and marketing and advancement functions of HEIs.

The rapid evolution and mass adoption of Large Language Models (LLMs) like ChatGPT, Microsoft Copilot, Google Gemini, Perplexity AI takes place in real time and presents challenges. As these tools quickly evolve and integrate, concerns arise over equity, inclusion, data privacy, transparency, ethics, plagiarism, bias, lack of robust regulations, need for AI literacy, fears of overreliance on technology, legal liabilities, and other unresolved issues, despite their widespread use globally.

The integration of AI tools in education requires immediate action from HEIs leadership, faculty, administrative staff and policymakers. This stimulates debates on AI tools benefits for educational stakeholders versus drawbacks and their impact on the educational landscape (Titareva, 2021). Discussions about AI tools in HEIs should not only focus on technological and business aspects but also address barriers to adoption, its impact within educational contexts, and essential skills for leadership in an AI-dominated era.

Definitions of Terms

This study examines the relationships between the key concepts of Artificial Intelligence (AI), AI in Education (AIEd), AI-based Early Alert Systems (EAS), Technology Leadership (TL) in Higher Education (HE), and Technophobia. While concepts of AI and AIEd introduce the topic of AI in HE; AI-based EAS, TL in HE, and Technophobia are the study's primary constructs.

Artificial Intelligence (AI). “A machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments. AI uses machine and/or human-based inputs to perceive real and/or virtual environments; abstract such perceptions into models; and use model inference to formulate options for information or action.” (OECD, 2019, p. 15). Further, OECD (2019) report describes

AI systems as tools predicting, recommending, or assisting decision-making across various sectors, including education, scientific research, digital security, criminal justice, marketing, and other sectors of the global economy. The report provides an example of AI tools like machine-assisted aids for the visually impaired. For example, in education, these tools can assist students by identifying physical objects on university campuses, as well as converting written text to audio, and transcribing verbally dictated text. Additionally, AI can assist in writing, improving lecture plans, as well as making more efficient the process of identifying, selecting and adapting study materials to the needs of diverse students (U.S. Department of Education, Office of Educational Technology, 2023).

AI in Education. An abbreviation of AI in education (AIEd) according to Issroff and Scanlon (2002) is an application of AI in the educational field in teaching and learning, as well management of administrative processes in HEIs. Additionally, Hwang et al. (2020) define AIEd as, "the use of AI technologies or application programs in educational settings to facilitate teaching, learning, or decision making [including administrative work in HEIs]" (p. 1). Some of the most common AIEd tools in teaching, learning and assessment include intelligent tutoring systems, chatbots to address students' questions and assist in teaching and learning, robot-graders, as well as augmented and virtual reality for course content acquisition and other functions. Additionally, AIEd tools are becoming more common in different administrative functions of universities such as: admissions, student services, libraries, advancement, marketing, and others (UNESCO IESALC, 2023).

Early Alert Systems (EAS). AI-based machine learning algorithms help to recognize, classify and predict the students' achievement in advance (Aybek & Okur, 2019), as well as to model student profiles to make predictions about their potential future performance. The term "early warning systems" (EWS) is also referred to as "early alert systems" (EAS) in more positive psychology contexts (Bentham, 2017; Cele, 2021; Dawson et al., 2017). EAS help to detect at-risk students in their first year or to predict the attrition of undergraduate students (Zawacki-Richter et al., 2019). EAS aim to detect early signs of potential student attrition and pass on these signals to faculty, advisors and administrators to support university retention efforts (Dwyer, 2017). By analyzing data of students' engagement in online learning (e.g., from learning management systems), the AI-based EAS can provide a visual dashboard with potential individual students' progress, upon which advisors and faculty could act to reduce dropout and increase retention rates (Araka et al., 2020). AI systems offer information and predictions about students' progress, but humans remain the ultimate decision-makers and act on this information (Barret et al., 2019). For example, the University of Tras-os-Montes e Alto Douro in Portugal launched an EDU.IA initiative that utilizes AI and data analytics to improve tutoring. By analyzing 15 years of academic records stored in a data warehouse, the system predicts students' future performances by comparing current and past grades (Silva et al., 2022). Similar strategies are used at the University of Canterbury in New Zealand to provide timely guidance from academic advisors (UNESCO IESALC, 2023).

Technology Leadership (TL) in **Higher Education** (HE). Originally, Anderson and Dexter (2005) defined educational technology leadership as a construct that "represents the organizational decisions, policies, or actions that facilitate effective utilization of information technology throughout the educational institution" (p. 80). This construct refers to the strategies, rules, and activities that the institutional leadership uses to ensure that technology is effectively integrated and utilized to support educational goals and processes across the entire organization. Furthermore, Yuting et al. (2022) validated a scale of technology leadership in higher education in China, which was also adapted and tested within this study. This scale comprises several subscales: equity and citizenship advocate, visionary planner, empowering leader, systems designer and connected learner. These two operationalizations of Technology Leadership (TL) in Education suggest that the traditional boundaries between strategic leaders and technological leaders in education have blurred. They are now interconnected. Both leaders, regardless of their IT or non-IT backgrounds and roles, are required to possess a combination of hard and soft skills and resources during the technology adoption process in educational institutions (Chowdhury et al., 2023). This evolution underscores the need for a holistic and collaborative approach to technology leadership in education.

Technophobia. “Fear, discomfort, or anxiety towards technology of various forms” (Hughes, 2010, p. 21; Khasawneh, 2015). Initially, technophobia was developed for testing fear and resistance toward computers. As technology has advanced, the nature and scope of technophobia have broadened. With AI-driven tools entering educational field around the world, many stakeholders, including HEIs’ leadership, faculty, and administrative staff, express anxiety and skepticism. This is often due to concerns about data privacy, potential biases in AI algorithms, or fear of unknown. Moreover, while early concept of technophobia might have been based on resistance to unknown, today's reality is more complicated. Concerns about AI surpassing human intelligence (coined as Artificial General Intelligence – AGI), making decisions without human intervention (McLean et al., 2023), or reducing human roles in education might increase feeling of technophobia. Also, the fact that AI-based tools develop faster than HEIs and educational policy makers can respond, makes it more challenging to address concerns and fears of the educational sector stakeholders (UNESCO IESALC, 2023).

Statement of the Problem

The rapid development and mass adoption of AI tools and growing field of AIEd highlights an urgent need for diverse research, new theoretical frameworks and testing different hypotheses (UNESCO IESALC, 2023). The research urgency stems from current system-level risks, concerns about future risks, and the potential for unintended consequences at scale, especially when AI-driven academic and administrative decisions might lead to negative outcomes (U.S. Department of Education, Office of Educational Technology, 2023). This research seeks to bridge the existing knowledge gaps, and equip educators and administrators in HEIs with insights and tools to navigate this transformative era effectively. Addressing these concerns now can help to prevent potential dangers, as well as maximize the positive impact of AI tools on the future of higher education.

Purpose of the Study

Higher Education Institutions (HEIs) are currently integrating advanced technologies, such as AI-based Early Alert Systems (EAS), which serve as additional tools in identifying and assisting students who may be at risk academically. However, the successful implementation and use of such tools depend on the adoption and use of EAS by the key stakeholders within HEIs, primarily the faculty and administrative staff. Thus, the main purpose of this study is to test quantitatively the potential influence of Technology Leadership (TL) in Higher Education (HE) and Technophobia on the Intention to Use Early Alert Systems (EAS) at HEIs by faculty and administrative staff members.

Rationale of the Study

Modern colleges have many diverse demands from different stakeholders (students, their families, local communities, boards of visitors, donors, and others) to achieve their institutional missions and student success with the same financial and human resources as before (Bartlett, 2020). Many institutions are looking for solutions in the reality of limited human resources and general defunding of universities (McGee, 2015; Popenici & Kerr, 2017) to handle extra work or cover vacant staff roles using emerging AI-based technologies (Barrett et al., 2019; Chatterjee & Bhattacharjee, 2020), including Early Alert Systems (EAS). AI-based EAS involves an initial significant financial investment but offers a long-term cost-effective solution that is scalable, provides additional data to faculty, advisors and administrative staff for decision-making, and supports student retention efforts. However, technology cannot be a stand-alone solution, it requires human intervention, leadership and change of culture (Arroway et al., 2016; Colvin et al., 2017; Tsai et al., 2019) for its long-term successful adoption and use by all stakeholders. Therefore, assessing technology leadership and factors like technophobia is important to evaluate the intention to use AI-based technologies in HEIs. The literature suggests that the intention to use technology often results in its actual use (Ajzen & Fishbein, 1974; FakhrHosseini et al., 2022).

Significance of the Study

This study increases the understanding of technology leadership, particularly within higher education context. The advancement of AI tools in HE has led to new challenges and opportunities for HEIs' leaders. As educational institutions around the world struggle with the rapid adoption and use of AI-based tools, there emerges a need to re-evaluate and redefine the concept of technology leadership in HE. Therefore, this study is significant for several reasons:

1) *Defining Technology Leadership in HE in the AI era.* While technology leadership in HE in the past has focused mainly on ensuring smooth operations and the adoption of necessary tools, the AI era demands a deeper understanding and strategic foresight. Technology leaders in HE now need to be equipped not only with the technical understanding about the AI tools, but also

with the ability to understand their broader impact on teaching and learning, assessment, administrative and operational functions of universities. This study highlights what it could mean to be a technology leader in higher education during the age of AI; 2) *Bridging the gap between the speed of AI technologies' introduction to the market and the adoption rate in HE settings*. Many higher education stakeholders, including HE leadership, administrative staff and faculty, are currently navigating a technological landscape that is evolving faster than traditional academic decision taking and adoption rates. There exists a gap between the speed of development and introduction to the mass market of AI tools, and the readiness or willingness of educational stakeholders to adopt and use them. This study attempts to identify the reasons for the existing gap in adoption of AI tools by different educational stakeholders (students vs. faculty and administration) that might help HE leaders to stimulate faster adoption of the emerging AI tools in a responsible and ethical manner; 3) *Consideration of Technophobia's influence on intention to use AI-based tools in HE*. By examining the role of technophobia, this study provides insights into additional reasons for HE staff's potential resistance, providing information to top leadership of educational institutions. While technophobia as a concept has been discussed and empirically tested in different fields, its impact on the adoption of emerging educational AI tools remains less explored. By testing the concept in a specific higher education institution in the southeast of the United States, this study offers a real-world case that could serve as a reference for consideration for other institutions globally. Understanding the origins, feelings and reasons behind technophobia toward AI-based tools can help HEIs implement more effective trainings and support mechanisms for their employees.

Research Questions

This study uses a quantitative approach to test the following research questions (RQs):

RQ1: To what extent does Technology Leadership (TL) in Higher Education (HE) influence faculty and administrative staff members' intention to use AI-based Early Alert Systems (EAS)?

RQ2: To what extent does Technophobia influence faculty and administrative staff members' Intention to use AI-based Early Alert Systems (EAS)?

Organization of the Study

The next chapter covers the literature review that describes major concepts and constructs and relevant technology adoption theories and models applicable to this study (Chapter 2). After I describe methodology of the study, including sample, data collection methods, measures used with their operational definitions, data cleaning and coding procedures, as well as statistical methods used in this study (Chapter 3). In the following chapter, I provide statistical analysis' results and their interpretation (Chapter 4). The final chapter provides a summary of the study, discussion about the findings, theoretical and practical implications for technology leadership in higher education, limitations and opportunities for the future studies, and conclusions (Chapter 5).

CHAPTER 2

This chapter reviews literature on: Artificial Intelligence (AI) and AI in education (AIEd), examples of AI tools' applications in higher education (HE), AI-driven Learning Analytics (LA) in HE, AI-based Early Alert Systems (EAS), Technology Leadership (TL) in HE, and Technophobia. The study's literature progression narrows from general concepts (AI, AIEd, AIEd applications in HE) to specific constructs relevant to the main study measures (TL in HE and Technophobia) and their impact on the intention to use AI-based EAS tools in HEIs. In the end, I describe dominant technology adoption theories and models relevant to this study and provide two study hypotheses.

Literature Review

Artificial Intelligence (AI) and Artificial Intelligence in Education (AIEd)

In 1950, British mathematician Alan Turing introduced the concept of machine intelligence, developing a test (now known as the Turing Test) to determine if a computer could mimic human thinking. At the same time, Claude Shannon explored teaching machines to play chess (Shannon, 1950). However, it was the Dartmouth Summer Research Project in 1956 where the foundations of AI discipline were discussed by innovators like J. McCarthy, A. Newell, A. Samuel, H. Simon, and M. Minsky. Despite early enthusiasm, AI advancements stagnated, resulting in an "AI winter" in the 1970s due to unmet expectations and decreased funding. Revival of interest and funding in AI field came back with advances in computational power that became available in the 1990s (University of Washington, 2006). During this decade, Richard Wallace's chatbot and IBM's Deep Blue, which defeated chess grandmaster Kasparov in 1997, marked significant milestone and recognition of AI tools' potential. By 2015, AI had further evolved with DeepMind's AlphaGo. Initially trained on human games, AlphaGo Zero surpassed all other versions of AlphaGo by outperforming its predecessors by training against itself, achieving mastery in 40 days without human input or past data. In 2016, AlphaGo won the top Go player – Lee Sedol – marking the milestone that AI tools can beat the strongest game player of one of the most complex board games (Google DeepMind, 2020). In recent years, exponential growth of the AI field took place due to the accumulation of big data, development of cloud computing, and innovations in machine learning, amplifying its impact and penetration on a global scale (OECD, 2019).

Chairman and Co-Founder of Coursera, Adjunct Professor at Stanford University and General Partner at AI Fund, Andrew Ng, states that AI has become integral to policymaking and research across global sectors. Just as electricity revolutionized industries over a century ago (Lynch, 2017), by 2023, nearly every industry discusses or considers incorporating AI tools in their daily operations. In higher education, there is significant anxiety about AI tools adoption among teaching and administrative staff, often stemming from limited understanding of the technology's advantages and drawbacks.

As Hinojo-Lucena et al. (2019) put it:

> AI has experienced major developments in recent years and represents an emerging technology that will revolutionize the ways in which human beings live. This technology is already being introduced in the field of higher education, although many teachers [and administrators] are unaware of its scope and, above all, what it consists of (p. 1).

Today's discourse on AI has shifted from a futuristic view to being a daily reality (Marr, 2019). Examples of AI in daily life include driverless cars, robots climbing stairs and opening doors, winning a television game Jeopardy, analyzing stocks, working in factories, advising medical specialists, and other (Aoun, 2017; Diamandis & Kotler, 2020). In 2023, in education are commonly used generative AI tools like OpenAI's ChatGPT, Microsoft' Copilot and Google's Gemini. These tools can create essays, poems, reports, and other content of reasonable quality (McCartney, 2023; McKinsey, 2023).

AI is an umbrella term and does not describe a single technology. The term refers to a range of technologies and methods that include machine learning, deep learning, neural networks, voice recognition, natural language processing, analytical and predictive statistics (Zawacki-Richter et al., 2019). In this study, I refer to the OECD (2019) definition of AI: "A machine-based system that can, for a given set of human-defined objectives, make predictions, recommendations, or decisions influencing real or virtual environments." I selected this definition from various options because it captures the essence of the AI technology relevant to this study – AI-based Early Alert Systems (EAS) in higher education.

Further, Hwang et al. (2020) define Artificial Intelligence in Education (AIEd) as "the use of AI technologies or application programs in educational settings to facilitate teaching, learning, or decision making" (p. 1). AI, including AIEd, is an interdisciplinary field that combines the fields of AI, science and education, psychology, neuroscience, linguistics, sociology, and anthropology (Becker, 2017; Luckin, et al., 2016). This broad definition of AIEd captures the essence of AI-based EAS in higher education, which I look at in this study.

Zawacki-Richter et al. (2019) highlight that AIEd has been one of the currently emerging fields both in general education and specifically in the field of educational technology. The application of AIEd has been the subject of research for over 30 years, however, the theoretical and empirical base is still at the incipient stage. Additionally, after the public release of ChatGPT 3.5 in November 2022 (OpenAI, 2022) and next version of ChatGPT 4.0 in March 2023

(Weitzman, 2023), HE faculty and staff started exploring how to leverage AI tools to improve their work. Empirical academic research in the AIEd field has become critically important.

Examples of AI Applications in Higher Education

Ciolacu et al. (2018) state, Education 4.0, characterized by artificial intelligence, big data, robotics, and the Internet of Things (IoT), is increasingly driven by AI technologies and tools. There is a rising demand for adaptive, personalized learning and a student-centric approach from HEIs stakeholders. Chatterjee and Bhattacharjee (2020) add, AI solutions have opened a range of possibilities for teaching, learning, and administrative tasks in higher education institutions. The integration of AI and related technologies into Education 4.0 represents not just an evolution but a revolution in higher education. As these tools become more sophisticated, HEIs that leverage them effectively will likely set new standards for educational excellence and innovation.

Given the vast amounts of student and operational data on university campuses, AI tools have potential to enhance administrative tasks, from financial aid to registrar’s office tasks. For instance, Arizona State University (ASU) uses AI tools to improve course descriptions, making them clearer for potential students and optimizing web search results (Selingo, 2023).

AIEd promotes a more flexible, personalized, and engaging learning environment (Luckin, et al., 2016; Southgate, 2020). At Georgia Institute of Technology, professor Ashok Goel used an AIEd tool as a teaching assistant to respond to students' email inquiries about assignments in his Artificial Intelligence class (Becker, 2017; Tedx SanFrancisco, 2016). As of 2023, AIEd technology, like the example at Georgia Institute of Technology, does not replace the professor. Instead, AI tools give faculty more time for tasks requiring creativity, emotional intelligence, and critical thinking, benefiting both teaching and administrative tasks.

Georgia State University (GSU) introduced a chatbot in an introductory government class to remind students about study habits and tasks. In result, researchers found a significant improvement in student performance. Especially, first-generation students acted on the chatbot's reminders, such as finishing assignments, at higher rates (Selingo, 2023). Page and Gehlbach (2017, 2018) investigated another AI tool in GSU called Pounce with students planning to attend the university. Results showed that students reached out by Pounce, completed pre-enrollment tasks and enrolled on time at higher rates than those with GSU's standard outreach (individual counselor and automated text-message outreach). In result, Pounce reduced GSU’s summer melt by 21%.

Another example of AI tools’ application in HEIs is Deakin University in Australia, where IBM’s supercomputer Watson provided student advising 24/7 addressing over 55,000 questions within the first year of adoption addressing such questions as “Where can I get food on campus?”, “Will I receive course materials for my cloud study?”, “How do I get a student card?” (Deakin University, 2015). Such tools help to meet the preferences of a digital generation of students who expect continuous messaging feedback anytime of the day and week (Barrett et al., 2019).

Moreover, AI tools offer a potential solution for handling student related questions (success, retention in separate courses and study programs). This comes as faculty and administrative tasks grow with the broader accessibility of higher education, despite declining government funding (Barrett et al., 2019; Thelin, 2019). AI-based solutions can generate data to highlight students at risk of leaving a course or university by evaluating factors like attendance, online behavior, and grades (Barefoot, 2004; Dwyer, 2017; Elbadrawy et al., 2016; Lester et al., 2017; Sweeney et al., 2015).

Bates et al. (2020) suggest that a promising use of AI technologies in higher education is learning analytics (LA) that produce early alerts, helping staff address student selection, dropout, and group behaviors. This data analysis can guide strategies for student retention, making administrative and teaching processes in HEIs more automated, efficient, and less inclined to human errors.

AI-based Learning Analytics' (LA) Adoption in Higher Education

The topic of Learning Analytics (LA) has increased in popularity among researchers due to the advancement of artificial intelligence (AI) and big data mining in the last decade. LA tools like educational data mining, visualization and predictive models provide useful individual and institution-wide information and recommendations to improve student success (Scheffel et al., 2014; Viberg et al., 2018). Simultaneously, HEIs are facing internal and external pressures for accountability (Bartlett, 2020; Kelchen, 2018; Norris & Baer, 2013), as well as are expected to provide customized student-centered teaching and administrative service approach, and proof of the learning outcomes (Austin & Sorcinelli, 2013; Bichsel, 2012; Klein et al., 2019). Hence, in higher education context, various LA tools began to emerge as solutions for data-driven decisions, improving the efficiency of teaching and administrative processes (Dahlstrom, et al., 2014; Klein et al., 2019; Norris & Baer, 2013).

The term "academic analytics" was introduced by Goldstein and Katz in 2005, which later evolved into "learning analytics" (Oster et al., 2016). The term of Learning Analytics (LA) became more common after its mention in the New Media Consortium (NMC) Horizon Report of 2012 (Johnson et al., 2012). A widely accepted definition of LA in both academic and practitioner circles comes from the Society for Learning Analytics Research (SOLAR). It has been introduced at the Learning Analytics and Knowledge (LAK) Conference in 2011 that is still relevant in 2024. SOLAR defines the LA term as the “measurement, collection, analysis, and reporting of data about students/learners to optimize the learning environment” (Friesen, 2013; SOLAR, 2023). In this study, I use this definition as it includes the core purpose of AI-based EAS within higher education - identifying students at risk of dropping out, thus helping universities in retention efforts.

In the higher education context, LA uses vast educational data to produce predictive analytics, generating visuals that help faculty, advisors and administrative staff monitor individual student progress and identify in advance potential progress risks for each student. Data for machine analysis and visualization can be sourced from students' Wifi access on the campus, logins to learning management systems (LMS), and ID card swipes for building access and meal purchases (Lester et al., 2017), as well as the number of forum posts in LMS, time spent on university's e-learning platforms, and assignment and course completion data (Elbadrawy et al., 2015; Klein et al., 2019; Sweeney et al., 2015). Campbell, Finnegan, and Collins (2006) analyzed student LMS activity and determined that LMS login data was a stronger predictor of course completion than prior academic indicators like SAT scores (Lester et al., 2017).

Purdue University's Course Signals (CS) was among the initial large-scale LA tools’ adopters in higher education. CS used real-time educational data, such as prior grades, demographics, and study efforts (like LMS logins and study time), to highlight students at risk of dropping out (Arnold & Pistilli, 2012). Purdue University's CS early alert system displayed dashboards, offering basic visuals for students and detailed views for faculty. The system utilized a traffic light system: red for at-risk students, amber signaling caution, and green - students on track for successful completion (Bañeres et al., 2020; Dawson et al., 2017).

The University of Maryland Baltimore County integrated a LA tool, Check My Activity, as part of their LMS (Fritz, 2013). Using the Check My Activity tool, students could compare their LMS logins' duration and grades to their peers. This approach was believed to motivate students to adjust their study behaviors, complete assignments, and ask for assistance, improving their academic performance in terms of grades (Pistilli et al., 2017).

Despite growing interest in LA tools in HE, empirical studies highlight barriers such as lack of resources and user training, institutional readiness, and compatibility with existing technologies (Arnold, et al., 2014; Bichsel, 2012; Klein et al., 2019; Macfadyen & Dawson, 2012; Norris & Baer, 2013). Additionally, the adoption of LA tools in HE progresses slowly due to HEIs' organizational challenges, such as traditional top-down decision-making and departmental silos (Baltaci-Goktalay & Ocak, 2006; Klein et al., 2019). Lastly, a lack of leadership support during technology adoption initiatives (Tsai & Gašević, 2017), and individual resistance like technophobia (Khasawneh, 2018; Kotze et al., 2016; Osiceanu, 2015), and factors such as age, gender, and education of users influence the intention and use of new technology (Venkatesh et al., 2003).

AI-based Early Alert Systems (EAS)

AI-driven learning analytics tools, such as Early Alert Systems (EAS), visualize predictions of student dropout or support needs in course materials' acquisition. Educational data mining involves classification, modeling, and prediction (Krishna et al., 2018; Zawacki-Richter et al., 2019). Early warning/alert systems are the next generation AI tools for predicting student performance. Analyzing early-semester online data can identify potential academic challenges, allowing for timely interventions helping to improve student progress (Akçapınar et al., 2019; Campbell et al., 2007; Johnson et al., 2006).

The term "early warning systems" was first introduced by Alexander Astin in the 1970s in relation to student attrition theories. To adopt a more positive connotation, institutions later started to refer to them as "early alert programs" (Lupack, 1983) and "early alert retention systems" (Rudmann, 1992). Early warning systems, initially designed to address student attrition, have evolved into early alert systems (EAS), reflecting a shift from a deficit mindset to a growth mindset with an aim to improve student engagement and success (Cele, 2021; Tinto, 2006).

AI-based EAS identifies at-risk students before they fall far behind, potentially preventing dropout or course withdrawal. It provides progress updates to faculty, administration, and students, encouraging communication for successful course, program or degree completion. In addition to individualized feedback, EAS generates data for informed decision-making on the institutional level (Ball, 2016). In this context, tools include predictive analytics, modeling (Bañeres et al., 2020; Bañeres et al., 2023), and recommendation systems utilizing machine learning (Bentham, 2017; Chung & Lee, 2019).

Within this study, I examine AI-driven Early Alert Systems (EAS) within Early Alert Programs (EAP). These systems offer early feedback to faculty, advisors, administrative staff, and students in HEIs, along with recommended actions to support student success (Dwyer, 2017). Such programs as EAP and tools like EAS help in student retention, quality improvement and personalized feedback (Oster et al., 2016).

LA tools like EAS face resistance from potential users, including faculty and administrative staff, due to their novelty (Aguilar et al., 2014) and limited adoption and understanding of the technology in many HEIs. Moreover, the introduction of LA tools often requires a shift in traditional approaches to teaching and managing administrative processes, which can further contribute to resistance. Faculty and staff may be accustomed to existing methods and may perceive the adoption of these new tools as disruptive or time-consuming. In result, overcoming these barriers and promoting acceptance and effective utilization of LA tools remains a challenge in many higher education institutions. Another challenge in LA adoption and use is the lack of systematic and effective data utilization (Scheffel et al., 2019). It can be partially explained by the siloed approach of operations of typical universities. Often, different departments and units within universities operate independently and may not readily share data or insights with one another. This siloed approach can hinder the holistic and coordinated use of data for the benefit of student success. To fully use the potential of LA tools, institutions need to address these structural challenges and promote a more collaborative and data-driven culture across the campus. One factor that could help to mitigate resistance to adoption of LA in HEIs is leadership and clear guidance in navigating the transition and adoption of AI and LA technologies, including EAS, within the higher education sector.

Data-driven decision-making has become a 21st-century reality, adopted by many organizations in different sectors. Nonetheless, it is important to recognize that while data visualization is a valuable tool, it should not be the sole basis for decisions in teaching and administrative work within HEIs. Human expertise, long-term vision, understanding of the broader impacts on the system and stakeholders (including students, faculty, advisors and administrators), and meaningful human interactions continue to play a crucial role in shaping final decisions (Kezar, 2018).

While LA and EAS holds the potential to improve the higher education environment, it also raises concerns among various stakeholders, including students, parents, faculty, and administrators. For example, in 2022, George Washington University (GWU) faced negative public reaction and had to apologize for collecting student data during Fall 2021 without prior consent or knowledge of the students (Smalley, 2022). This incident highlights the thin line between leveraging LA for educational process improvement and ensuring the protection of individual privacy rights. It shows the importance of transparent data collection and use practices in higher education to build trust among stakeholders and maintain ethical standards in the evolving landscape of learning analytics. The absence of a comprehensive framework and guidelines for responsible AI tools' adoption set by university leadership can leave institutions struggling with ethical and privacy challenges, further emphasizing the need for proactive leadership in this transformational journey.

Technology Leadership (TL)

As stated at the World Economic Forum (WEF) in Davos in 2016, we are not experiencing a technology crisis but rather a technology revolution of historically unprecedented scale, characterized by remarkable technological progress (Barnato, 2016). Hence, the statement refers to Industry 4.0, often termed as "the fourth industrial revolution" (Schwab, 2017), associated with AI-based technologies and solutions, including cloud computing, big data, machine learning, and neural networks. In the context of leadership in disruptive technology innovation times, understanding and utilizing these transformative technologies becomes crucial for leaders in navigating the shifting landscape of Industry 4.0.

The first e-leadership definition has been introduced by Avolio, Kahai and Dodge in 2000 when the authors defined the term as follows:

> E-leadership is as a social influence process mediated by Advanced Information Technology (AIT) to produce a change in attitudes, feelings, thinking, behavior, and/or performance with individuals, groups, and/or organizations (p. 617).

Years later, Avolio et al. (2014) updated the e-leadership definition further expanding on the context where e-leadership takes place:

> E-leadership is a social influence process embedded in both proximal and distal contexts mediated by AIT that can produce a change in attitudes, feelings, thinking, behavior, and performance (p. 107).

In general, the definitions above cement the technology as central part of leadership (Gurr, 2004). Moreover, in the early 2000s the essence of e-leadership primarily focused on effectively leading geographically diverse virtual teams (DasGupta, 2011). Lastly, it is important to note that the concept of e-leadership emerged during the era of Information and Communication Technologies (ICT) of the Industry 3.0, where leadership was influenced by the dominance of computers, laptops, smartphones, social networks, and other technologies that at the time transformed work and communication. However, today these technologies have become commonplace and have given way to the dominance of Industry 4.0 technologies, characterized by artificial intelligence, big data, full process automation, Internet of Things (IoT), cloud computing, robotics, and more.

Since the first introduction of the concept of "e-leadership", the term has been used interchangeably as ICT leadership (Yee, 2000), Information Technology (IT) leadership, digital leadership, online leadership (Hollingsworth et al., 2004), technology leadership (Anderson & Dexter, 2000, 2005), educational technology leadership (Kearsley & Lynch, 1994), and others. Technology leadership, the central concept of this study, encompasses wider range of technologies than ICT or IT leadership (Tan, 2010). It involves leadership in conjunction with technologies such as artificial intelligence, blockchain, cloud computing, and virtual reality (Al-

Ghnimi et al., 2022), Internet of Things (IoT) and device-to-device communication (Karakose et al., 2022).

Technology leadership has been a subject of research in the US since the 1990s. It is widely recognized that effective technology leaders must possess a combination of technical expertise and leadership skills (Hurt et al., 2014). Furthermore, technology leaders are tasked with considering not just the technical adoption of IT tools but also considering the vision, mission, and university goals, along with effective communication with internal and external stakeholders, and providing training and support to employees on the utilization of new age technologies (Flanagan & Jacobsen, 2003; Hickman & Akdere, 2017; Keengwe et al., 2009; Miller, 2019).

Anderson and Dexter (2005) define educational technology leadership as a construct that contains “the organizational decisions, policies, or actions that facilitate effective utilization of information technology throughout the educational institution” (p. 80). According to the authors, their study results showed that despite the fact that technology infrastructure is salient, technology leadership is more effective and important for the integration and use of new technologies in educational institutions than infrastructure alone. Compared to e-leadership where ICT/technology was a central tenet of leadership, Anderson and Dexter’s (2005) definition of technology leadership reflects more strategic functions of leaders and leadership processes that help in technology enhancement and use in educational institutions. Modern technology leadership and its related definitions (IT/ICT/digital leadership) place greater emphasis on people and users rather than technology alone (Qian & Huang, 2019). In this context, technology leaders play a pivotal role in guiding departments, organizations, and followers toward technological transformation at the institutional level, as opposed to the individual or team level (Ratajczak, 2022). Anderson and Dexter (2005) emphasize the significance of various technological components during the adoption of new age technologies. Nevertheless, they highlight that technology leadership holds equal importance when it comes to ensuring technology's sustained use by all relevant educational stakeholders in the long term.

Recent research in China by Yuting et al. (2022) underscores the need for appropriate frameworks to assist leaders in effectively practicing technology leadership in higher education. The authors use the ISTE Standards for Education Leaders (ISTE, 2018) as a widely recognized global standard used for assessing technology leadership in education. The standards elaborate on the essential qualities of technology leaders, encompassing five key practices: equity and citizenship advocate, visionary planner, empowering leader, systems designer, and connected learner. While scholars have predominantly focused on educational leaders' vision for technology utilization and their supportive roles in the ICT integration process, it is equally important to consider how technology leaders create an environment helpful to technology adoption and learning (Dexter & Barton, 2021).

Technology Leadership (TL) in Higher Education (HE)

Nonprofit association EDUCAUSE striving to advance higher education through the use of IT, highlights that artificial intelligence (AI) has been influencing HE IT departments’ role in being mission driven, agile and increasingly influenced by global technological changes (Steinour et al., 2018; Qian & Huang, 2019). In result, the term University 4.0 has emerged in association with Industry 4.0 technological progress (Asabin et al., 2019; Lapteva & Efimov, 2016; Lukovics & Zuti, 2017). University 4.0 signifies radical transformational changes in modern HEIs. It goes beyond viewing new technologies solely as pedagogical tools and, instead, recognizes them as a part of global revolution that impacts various dimensions of modern universities.

Most of the universities around the world are still living in Industry 2.0 (mass production and electricity) and Industry 3.0 (electronic and IT systems and automation) versions. For HEIs to move to Industry 4.0, the process requires not only adoption of new age technologies but also new ways of leadership and followership and transition through transformational technological change and change of culture (Rocha et al., 2021; Wallace et al., 2011). Technology leaders in University 4.0 should consider both technology and higher education (Yuting et al., 2022).

Technology leadership research in universities currently is in its inception stage (Ratajczak, 2022). Technology alone does not enhance the value of higher education institutions, it requires technology leaders who can lead the overall digital transformation of the entire campus and foster a cultural change. This transformation includes the adoption of innovative emerging technologies, such as AI, blockchain, and the Internet of Things, within higher education. Ultimately, these technologies reshape activities and streamline processes related to the institutional mission, enhancing user experiences and overall satisfaction (Miller, 2019).

When it comes to the adoption of AI-based tools like EAS in HEIs, current adoption models indicate that achieving widespread adoption of AI-based technologies in HEIs requires leadership capable of fostering collaboration among various HEIs' stakeholders. This leadership should align actions with institutional strategic planning, develop policies for effective data management, and cultivate a culture that maintains a balance between innovation and operational stability (Colvin et al., 2015; Ferguson et al., 2014; Tsai et al., 2018; Tsai et al., 2019).

Given often siloed nature of operations within HEIs, the widespread implementation of AI-based tools in higher education demands a specific set of leadership skills. As the higher education landscape changes, introducing new technologies such as AI-based tools, numerous studies indicate that modern leadership in HEIs should shift away from a hierarchical, leader-centric model toward a more participatory and collective institutional governance approach. This transition redirects focus from individual leaders to organizational processes (Bento, 2011; Dumas & Beinecke, 2018; Tsai et al., 2019). Hence, this study examines the necessary technology leadership skills that have the potential to mitigate faculty and administrative staff's fear (technophobia) of new technologies, and positively influence their intention to use AI-based EAS in HEIs.

Addressing the human aspect of technology leadership in the context of the Industry 4.0, Jones (2018) emphasizes the coexistence of AI and leadership, though with some modifications. Leadership will evolve to place greater emphasis on data, and decision-making processes will involve fewer individuals due to the change of job tasks and workforce reskilling. The main outcomes, however, will remain unchanged. AI tools will prove most advantageous to leaders who invest in studying, understanding, and effectively utilizing them. Additionally, Brock and Wangenheim (2019) offer a balanced perspective on the coexistence of AI and leadership. In their article, they state that while AI holds significant promise, it is not a universal panacea. The authors encourage to explore the emerging discipline of AI leadership and the role of AI leaders of the future. Lastly, Shukla et al. (2017) encourage future leaders to cultivate a culture that enables employees to thrive alongside intelligent machines. This aligns with the central idea of this study: that leadership and technology, while valuable individually, must be integrated into a unified concept - AI technology leadership.

What distinguishes AI technology leadership from other forms of technology leadership is its unique capacity to navigate and utilize the potential of AI tools. Unlike classical technology leadership, AI technology leadership requires a deep understanding of AI's complexities, its ethical implications, and its transformative impact on organizations and industries. It involves not only managing technology adoption but also shaping a culture that smoothly integrates human and AI capabilities, and ensuring ethical and responsible AI practices. AI technology leaders are required to have the vision to strengthen AI tools' capabilities, drive digital transformation, and guide HEIs toward sustainable success in the AI era.

Technophobia

Technophobia, often referred to as the fear or anxiety associated with technology, is one of the primary reasons for technology avoidance or non-adoption (Kotze et al., 2016). An overarching definition of technophobia relevant to technologies of Industry 4.0 is, "Fear, discomfort, or anxiety towards technology of various forms" (Hughes, 2010, p. 21; Khasawneh, 2015).

Technophobia can be divided into three categories: 1) internal resistance toward technological change; 2) fear or anxiety of the actual or potential use of new technology; and 3) hostile attitudes toward a wide range of emerging technologies (Brosnan, 1998; Nestik et al., 2018). In essence, technophobia plays a crucial role in distinguishing between technology adopters and non-adopters (Sinkovics et al., 2002), encompassing both individual and societal attitudes toward technology (Osiceanu, 2015).

Technophobia has a long history, with early recognition dating back to Plato in approximately 400 BCE. Plato's concerns were related to the introduction of writing, which he feared would lead to a decline in human memory as ideas were written rather than memorized. Similar fears were related to the printing press in c1400s (Dittmar, 2011), phones in 1800s (Parker, 1995), TV in 1960s (U.S. Department of Education, 1982), personal computers in 1980s

(Rosen & Sears, 1987), WiFi in 1990s (Goldsworthy, 2011), smartphones in 2000s (Elhai et al., 2017; Richardson et al., 2018), and other technologies (Davidson et al., 2019). Hence, it is unsurprising that in the post-2020 era, individuals express anxiety and concerns about technologies having the label of AI. Though, from a technological standpoint, current AI tools, particularly in higher education, are generally categorized as "weak" or “narrow” in terms of their capacity and autonomy from human control (Zawacki-Richter et al., 2019).

As humans struggled with technophobia, triggered by events such as the Industrial Revolution in the early 20th century, the development of atomic technology in the mid-20th century, and the rise of AI technologies in the 21st century, additional reasons for the anxiety emerged. These include: fears of job displacement, the automation and substitution of labor-intensive tasks, as well as the potential for technogenic and ecological catastrophes (Nestik et al., 2018) and that machines can supersede human race with advanced artificial intelligence.

From a psychological perspective technophobia is a more nuanced construct that includes not only logical, but also cognitive, emotional and behavioral layers of human perceptions, feelings and behavior (Gilbert et al., 2003; Nestik et al., 2018). Several studies have found a direct effect of technophobia on behavioral intention (Koul, 2017; Madden et al., 1992; Parker et al., 1992) that is considered a predictor of technology use behavior (Ajzen & Fishbein, 1974; FakhrHosseini et al., 2022; Lai, 2017). The common predictors of technophobia in empirical studies are considered: gender and age (Brosnan, 1999; Gilbert et al., 2003; Hogan, 2008; Khasawneh, 2015; Korukonda, 2005; Kotze et al., 2016; Koul, 2017; Nestik et al., 2018), where in many cases female and elder people have been considered to have higher levels of technology anxiety than male and younger people, as well as educational level with lower level of technophobia generally attributed to those with higher level of education (Marescotti, 2021).

This study contributes to the existing body of research by examining technophobia from a broader psychological perspective, exploring its potential influence on the behavioral intention to use AI-based technologies of EAS in HEIs. Additionally, many of the previous studies have focused on technophobia in the context of specific technologies, primarily computers. There is a lack of validated technophobia measurement instruments that can be applied to AI tools in general and AI-based EAS in HEIs specifically. Lastly, technophobia remains an underutilized construct in explaining users' intentions to use (or resist to use) technology (Khasawneh, 2018).

After providing literature review above related to the key concepts and constructs of this study, including AI, AIEd, Technology Leadership (TL) in HE, and Technophobia and their potential influence on the intention to use AI-based EAS tools in HEIs, the next section provides overview of the main technology adoption theories and models.

Technology Adoption Theories and Models Related to Intention to Use Technology

The **Theory of Reasoned Action (TRA)**, formulated by Fishbein and Ajzen in 1975 in the field of social psychology, was designed to predict human behavior in technology use. TRA refers to attitude and intention to act by an individual (Gilbert et al., 2003). One of the main assumptions of this theory is that behavioral intention predicts behavior itself (FakhrHosseini et al., 2022; Lai, 2017). In the context of AI-based EAS adoption in HEIs, where currently faculty and administrative staff may not be fully aware of the technology's potential, predicting their intention to technology use becomes an essential first step. It is considered that one of the main limitations of TRA is its narrow applicability when potential users are mandated to use the technology, as their choice is not voluntary. Further, an improved version of TRA, the Theory of Planned Behavior (TPB), was introduced by Ajzen in 1991 (Teo & Schaik, 2012).

The **Theory of Planned Behavior (TPB)** extends the predictors of behavioral intention from the Theory of Reasoned Action (TRA). TPB explores various factors that can impact an individual's intention to change, such as attitudes and perceptions that either facilitate or delay the adoption of technology. The main assumption of TPB is more favorable attitude and subjective norm an individual has toward potential behavior in technology use, the larger is expected to be the behavioral control that leads to stronger intention of an individual to have the expected behavior in technology use (Pierce & Ball, 2009). TPB contradicts TRA main assumption that there might be situations when strong technology use intentions do not lead to actual use of technology (Ajzen, 1991; FakhrHosseini et al., 2022; Wahdain & Ahmad, 2014). TPB is an established technology adoption framework in social sciences research (Pierce & Ball, 2009).

Technology Acceptance Model (TAM) has been developed by Fred D. Davis (1989) for application specifically explaining behavior in using computers. Unless TRA and TPB that are used to test intention to use technology on individual level, TAM and its successor, Unified Theory of Acceptance and Use of Technology (UTAUT), are widely recognized models, often referred to as theories, that include various dimensions of technology adoption, including the user, tasks, system, and context. The main assumption of TAM is that constructs of perceived ease of use (PEU) and perceived usefulness (PU), are predictors for behavioral intention of technology use (Dishaw & Strong, 1999). In the early version of TAM, the attitude was a mediating variable between PEU and PU and mediated the path between PEU and PU and intention to use technology. Original application of TAM was meant for studying the actual use of IT systems, where the use was voluntary (Dishaw & Strong, 1999; FakhrHosseini et al., 2022). TAM that has adapted theory of reasoned action (TRA) by Fishbein and Ajzen (1975), is considered to be a reliable model for explaining the technology use behavior (Godoe & Johansen, 2012; Malhotra & Galletta, 1999; Yi & Hwang, 2003). Since 1989, TAM has been validated and extensively employed in empirical research on technology adoption (FakhrHosseini et al., 2022; Legris et al., 2003; Peek et al., 2014; Wahdain & Ahmad, 2014).

Unified Theory of Acceptance and Use of Technology (UTAUT) developed and published by Viswanath Venkatesh, Michael G. Morris, Gordon B. Davis, and Fred D. Davis in 2003. UTAUT is one of the most commonly applied technology adoption models that has been empirically tested for its applicability in assessing the intention to use technologies across various fields, including higher education (Chatterjee & Bhattacharjee, 2020). The UTAUT model explains the users' intention to use (behavioral intention) an IT system and user's behavior in using it (use behavior) (Chen, 2019). The instrument is measuring four moderating variables: gender, age, experience, and voluntariness of use (whether the use is voluntary or mandatory) of technology users. Also, the UTAUT instrument measures the mediating variable – behavioral intention – BI (whether users are planning to use new technology). Lastly, the model measures the dependent variable – use behavior – UB (behavior of potential users when the technology is adopted).

To summarize, the first two theories, TRA and TPB, were initially developed in the field of social psychology to predict human behavior and behavioral intention regarding technology use. TRA assumes that behavioral intention (BI) predicts subsequent technology use, aligning with a key assumption of this study. TPB explores attitudes and perceptions that influence the intention to use technology, which is a central focus of this research. Furthermore, the two most widely cited and empirically tested technology adoption models, TAM and UTAUT, consider various aspects of technology adoption systems, context, and individual characteristics of users, such as age and gender in predicting the intention to use technology—labeled as "Intention to Use AI-based tools in HEIs" within this study. TAM has adopted TRA and UTAUT – both TRA and TPB.

Building upon the constructs of established technology adoption theories and models above, this study takes an proactive approach to examine the potential impact of two new constructs—Technology Leadership in Higher Education (TL in HE) and Technophobia — on the Intention to use AI-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs).

Thus, the study **hypotheses** (H) are:

H1: Technology Leadership (TL) in Higher Education (HE) is expected to have a direct positive effect on the Intention to Use AI-based Early Alert Systems (EAS) by faculty and administrative staff members at Higher Education Institutions (HEIs).

H2: Technophobia is expected to have a direct negative effect on the Intention to Use AI-based Early Alert Systems (EAS) by faculty and administrative staff members at Higher Education Institutions (HEIs).

Summary. This chapter provided an overview of the literature relevant to the key constructs and concepts of this study, discussed relevant theories and theoretical models, and concluded by presenting the study hypotheses. The next chapter looks into how these proposed constructs and their relationship have been measured and analyzed within this study.

CHAPTER 3

Methods

Introduction

This research was conducted collecting and analyzing data from a mid-size higher education institution in the southeast of the Unites States. With this study I was interested in facilitating discussion about a topic of the Technology Leadership in AI Era within the context of higher education.

The primary purpose of this study was to test quantitatively the potential influence of Technology Leadership (TL) in Higher Education (HE) and Technophobia on the Intention to Use AI-based Early Alert Systems (EAS) at HEIs by faculty and administrative staff members. This study can be best characterized as a quantitative study in a single institution of higher education.

The study addresses the following research questions (RQ): RQ1: To what extent does Technology Leadership (TL) in Higher Education (HE) influence faculty and administrative staff members' intention to use AI-based Early Alert Systems (EAS)? RQ2: To what extent does Technophobia influence faculty and administrative staff members' Intention to use AI-based Early Alert Systems (EAS)?

The quantitative method was chosen for this study for several reasons. From theoretical perspective, quantitative methods, in general, give more opportunity for the results to be generalizable to a larger population; quantitative methods provide clear parameters for the study and are helpful in hypothesis testing. From a practical perspective, surveys as an instrument of quantitative method, can be distributed to a larger number of respondents, covering a wide range of experiences and perspectives within HEIs; a quantitative study provides numerical data that can be used to inform institutional practices; quantitative data, being numerical, can be precisely measured and interpreted (Creswell & Creswell, 2018; Privitera, 2019), thus providing clear indicators for institutions about where they stand in terms of technology leadership skills of the respondents' leaders and level of technophobia toward AI tools of the administrative staff and faculty.

Additionally, as per synthesis of literature by Ratajczak (2022), the most common method used in empirical studies (50%) on academic technology leadership published in Scopus and Web of Science from 2013 to 2022 was quantitative. Also, the quantitative method with the help of the questionnaire for testing the existing measures of the constructs of this study has been chosen based on the most common data collection method used in the empirical studies of Chatterjee and Bhattacharjee (2020), Davis (1989), Khasawneh (2015), Liu et al. (2018), Masrur (2021), Teo and Schaik (2012), Venkatesh et al. (2003), Yuting et al. (2022) that previously validated the main constructs of the Technophobia, Technology Leadership in HE and Intention to Use Technology.

In this chapter I am introducing the methodology of the study. The chapter is organized into the following sections: Study Sample, Data Collection Methodology, Measures, Data Cleaning and Coding, and Statistical Analysis.

Sample

A convenience sampling method was utilized to ensure a representation of faculty and administrative staff members at the selected HEI. The total sample of this study with completed and usable responses was 222 coming from one higher education institution in the southeast of the United States. The response rate for the sample reached 72.55% completion rate.

The final sample respondents' demographic breakdown was as follows. Gender: 53.2% identified as women, 41.9% - as men, and 5% - as other, including non-binary, agender, gender fluid, gender queer, or no answer. Age: respondents ranged in the age from 22 to 73 years. Role within institution: 55.9% identified as administrative staff, while 44.1% were faculty members, dedicating over 60% of their working time to the respective role. Highest level of completed educational degree: 17.6% of respondents held bachelor's degrees, 27.9% had master's degrees, 46.8% - doctorate degrees, 2.7% - professional degrees, and 5% - other degrees. STEM (science, technology, engineering, and mathematics) background: 26.1% of respondents had STEM degrees, while 73.9% - did not.

Data Collection Methodology

The finalized survey measurement tool (see Appendix E) comprises 43 items split into four main sections: 1) Technophobia (7 questions based on validated instruments by Khasawneh, 2015, 2018), 2) Technology Leadership in Higher Education (21 questions from Yuting's et al., 2022 validated instrument), 3) Intention to Use AI-based Early Alert Systems at HEIs (3 questions adapted from Teo & Schaik, 2012, and the Harvard White Paper, June 2020), and 4) Demographics (12 questions).

After the dissertation proposal defense, I contacted the original authors of the measurement instruments of Technophobia and Technology Leadership in Higher Education and obtained their permission to adopt and use the instruments within my study (e-mail to the authors and their approvals - Appendix A). As the next step, I have obtained the Institutional Review Board (IRB) approval for my study within HEI where the study has been conducted (Appendix B).

The data collection took place between June 21 and August 28, 2023, when a survey link to QuestionPro was distributed thrice to JMU staff and faculty in the following way. The initial request to distribute the survey across the campus was sent out through my personal contacts in the departments of Student Affairs, Academic Affairs, Research and Scholarship, Libraries, Registrar's Office, IT department of the College of Business (COB), as well as COB administration and faculty lists, university Advancement, the College of Science and Mathematics (CSM), the College of Education, Graduate School, university Marketing, Social Justice Studies department, faculty of Biology, Nursing, Psychology, Political Science, Technical Writing and Rhetoric, and Community Service Learning. After obtaining slightly more than half of minimally required responses (around 100), I have noticed that the completed responses had less of faculty and administrative staff representing STEM colleges and departments. The second outreach was directed to specific representatives from the university staff directory representing departments of Computer Information Systems, Computer Science, Computer Science - Technology Talent, College of Integrated Science and Engineering, Digital Marketing, Educational Technology and Media Center, IT and Computer Labs, IT and Computing Support, IT and Information Systems, IT and Technical Services, Integrated Science and Technology, Learning, Technology & Leadership Education, Student Affairs Technical Service. When the response rate reached 164, I have approached the same university employees as in the first round and asked to share in different channels the reminders about the survey. The survey has been distributed to 991 recipients. Of these, 306 began the survey and 222 completed it. The average time taken for individual response was 9 minutes.

Measures

The key measures used in this study are measures of constructs of Technophobia, Technology Leadership in HE and Intention to Use AI-based EAS at HEIs, as well as control variables of age, gender, role in university, level and field of education. The operational definitions of major constructs are provided next.

The *independent variable 1* – **Technophobia of AI in HEIs** – is defined as "fear, discomfort, or anxiety towards technology of various forms" (Hughes, 2010, p. 21; Khasawneh, 2015; Khasawneh, 2018). The measurement instrument for Technophobia of AI in HEIs has been adapted and modified from the technophobia measurement instrument validated by Khasawneh (2015, p. 145). In the study, reliability coefficient of Cronbach's alpha for the general construct of Technophobia was 0.898 (Khasawneh, 2015; Khasawneh, 2018).

The *independent variable 2* –**Technology Leadership (TL) in HE** has been defined as a construct that "represents the organizational decisions, policies, or actions that facilitate effective utilization of information technology throughout the educational institution" (Anderson & Dexter, 2005, p. 80). The measurement instrument for Technology Leadership (TL) in the context of higher education in China has been adapted and modified for the context and purpose of this study from Yuting et al. (2022, p. 10303), where authors developed their instrument based on ISTE Standards for Education Leaders (ISTE, 2018). ISTE standards is globally recognized benchmark for assessing technology leadership, which also serves as a guide for relevant training, and detailing the essential characteristics of technology leaders. TL construct in HE context consists of the following five sub-scales: Equity and Citizenship Advocate, Visionary Planner, Empowering Leader, Systems Designer, and Connected Learner. Yuting's et al. (2022) empirical study results showed Cronbach's alpha for each of five sub-scales of TL ranging from

0.834 to 0.881. In Yuting et al. (2022) study the authors tested TL influence on teaching performance or outcomes. In my study, I have tested the tool to measure TL influence on Intention to Use AI-based tool of EAS within HE context.

Dependent variable – **Intention to Use (ITU) AI-based EAS at HEIs** has been developed from constructs of "intention to perform the behavior" in the Theory of Reasoned Action (TRA) and "Intention" in the Theory of Planned Behavior (TPB), as well as "behavioral intention to use" in TAM and "behavioral intention" in UTAUT technology adoption models. Behavioral intention is defined as "the strength of one's intention to perform a specified behavior" (Fishbein & Ajzen, 1975; Blut et al., 2022, p. 89). TRA states that intention to use is positively related to an individual's later technology use behavior (Lotfizadeh & Ghorbani, 2015). As AI-based EAS is still very new in HE environment and evaluating its actual use is difficult due to the lack of the technology in place in most of the HEIs, instead the intention to use the technology has been measured within this study. The measurement instrument for Intention to Use AI-based EAS at HEIs has been adapted and modified from the measurement instruments by Teo & Schaik (2012, p. 188) and Harvard White Paper (June 2020) "Strategic Data Use in Higher Education" (p. 13) (operationalization of the instrument - Appendix E).

Control variables used in this study include variables of: **gender** and **age** that have been empirically tested by Venkatesh and Morris (2000) and hundreds of other studies on technology (intention) adoption (Afshari et al., 2009), as a basis using either TRA or TPB theories, as well as additional control variables relevant to the field of higher education: **role** of respondents within HEI (faculty vs. administrative staff), **terminal degree level** (bachelor's, master's, doctorate, professional and other) and **terminal degree field (STEM/non-STEM background)** with assumptions that STEM/non-STEM respondents might have different attitudes toward intention to use AI-based tools in HEIs (Demirci & Ersoy, 2008; Koul, 2017; Rojas-Méndez et al., 2017).

Gender is defined as “gender of the user” (Blut et al, 2022, p. 90). There is a stream of research that states that gender does have an influence on use or intention to use technology. This stream believes that male more than female are technology savvy, have more advanced information and communication technology (ICT) skills, are more eager to adopt new technological devices, as well as exhibit higher self-confidence in using [intending to use] new technology (Gilroy & Desai, 1986; Gutek & Bikson, 1985; Harrison & Rainer, 1992; Rojas-Méndez et al., 2017; Tsikriktsis, 2004). Contrary, there is also a research stream that gender does not significantly influence adoption and use (or intention to use) of technologies and digital products (Fram & Grady, 1997; Li et al., 2008; Rainer et al., 2003; Rojas-Méndez et al., 2017; Shaw & Gant, 2002). Opposing findings of both streams have motivated me to include the variable of gender as a control variable to test within this study in higher education settings. In general, gender is found to be an important variable in acceptance, adoption, or the intention to use technology (King & He, 2006; Şahin & Şahin, 2022; Tarhini et al., 2014; Venkatesh et al., 2003). The gender items for this study have been adapted from the brochure “More than numbers: Guide Toward Diversity, Equity, and Inclusion (DEI) in Data Collection” by Charles and Lynn Schusterman Family Foundation (2020, p. 32).

Age is defined as “the age of the user” (Blut et al, 2022, p 89). Age has been considered to be an important moderator in adoption (or intention to adopt and use) of innovations (Rogers, 1995) and technology (Hertzog & Hultsch, 2000; Rojas-Méndez et al., 2017; Venkatesh et al., 2003). The previous research has found that age is considered to be negatively related to adoption (or intention to adopt and use) of innovations and technologies (Harrison & Rainer, 1992; Nickell & Pinto, 1986; Tsikriktsis, 2004).

Education that has been considered to be a significant predictor of individuals' tendency to adopt and use new technology (Rojas-Méndez et al., 2017) has been operationalized within this study as **terminal degree level** (measurement adapted from National Survey of College Graduation: 2021, NSF 23-306, p. 7 – 10) and **field of the terminal degree** (STEM/non-STEM background). In general, the previous studies have found that people with lower educational attainment have higher technology anxiety (Igbaria & Parasuraman, 1989), have restricted ability to acquire new knowledge (Hilgard & Bower, 1975) and negative relationship between the level of education and the perceived ease-of-use of new technology (Porter & Donthu, 2006). Additionally, due to the context of higher education, within this study I have added a control variable - **role** (faculty vs. administrative staff) - to account for differences in perceptions about technology leadership and new technology adoption due to different specifics of job tasks of instructional vs. non-instructional staff and the differences in their leaders.

Data Cleaning and Coding

Data Cleaning. In the study analysis, 222 surveys were fully completed. The responses were imported from QuestionPro into an Excel spreadsheet. Missing data was identified for several variables. The "Age" category had two missing values. 128 "College" values were absent, mainly from respondents who identified with administrative roles (attributing to this role over 60% of their annual workload). On the other hand, 94 "Administrative department" entries were missing, mainly from those who identified primarily as faculty (also over 60% of their annual workload). The missing values were left blank and were not included in the final analysis.

The "field of terminal degree" had 11 missing entries, which were grouped under the "another major" category, eliminating any blanks for this variable.

Data coding. For the data coding and analysis, I used IBM SPSS v 29. The following steps describe the coding procedures implemented.

For data coding of *independent variable 1* – **Technophobia of AI in HEIs**: I used seven items (Appendix E). Each was coded on a scale from 1 to 5 (*1 – disagree, 2 – slightly disagree, 3 – neither agree/disagree, 4 – slightly agree, 5 – agree*). A composite score, labeled *Total Technophobia Value*, was calculated by average sum score. This measure was meant to provide an overall understanding of survey respondents' resistance or openness to use AI-based EAS in the HEI where the study has been conducted.

For data coding of *independent variable 2* – **Technology Leadership (TL) in HE** was divided into five sub-scales: 1) Technology Leader Equity and Citizenship Advocate measured by four items; 2) Technology Leader Visionary Planner measured by five items; 3) Technology Leader Empowering Leader measured by five items; 4) Technology Leader Systems Designer measured by four items; and 5) Technology Leader Connected Learner measured by four items (operationalization of each sub-scale – Appendix E). Each of TL in HE sub-scales and their respective items were coded in SPSS from 1 to 5 (*1 – disagree, 2 – slightly disagree, 3 – neither agree/disagree, 4 – slightly agree, 5 – agree*).

A composite score, labeled *Total Leader Equity and Citizenship Advocate*, was calculated by average sum score of items measuring this sub-scale of Technology Leadership (TL). Similarly, were calculated values for TL sub-scales of *Leader Visionary Planner, Leader Empowering Leader*, *Leader Systems Designer* and *Leader Connected Learner*. In the end, the

TL in HE value was calculated as the average sum score of the five TL sub-scales above and labeled as *Total Technology Leadership Value*.

Dependent variable of **Intention to Use (ITU) AI-based EAS at HEIs** was measured by two items (operationalization of items – Appendix E), where each item was coded in SPSS from 1 to 5 (*1 – disagree, 2 – slightly disagree, 3 – neither agree/disagree, 4 – slightly agree, 5 – agree*). The total ITU value was calculated as the average sum score of the two items and labeled in SPSS as *Total Intention to Use Value*. The last item for ITU was an open-ended qualitative question and was formulated based on example from Harvard White Paper (June 2020) "Strategic Data Use in Higher Education": *"What else do you think we should know that we haven't asked you about in relation to the intention to use AI-based EAS at JMU?"* Responses to this question helped to identify the themes and codes that were relevant to the construct of intention to use AI-based tools at HEI (Appendix F).

Other variables used in the analysis were coded as follows. *Gender* was coded into three categories: 1 – woman, 2 – man, 3 - non-binary, agender, gender fluid, gender queer, prefer not to answer. *Age*: number of full years. *Role*: 1 – faculty, 2 – administrative staff. *Terminal degree level*: 1 - Bachelor's, 2 - Master's, 3 - Doctorate, 4 – Professional, 5 – Other. *Field of terminal degree (STEM/non-STEM)*: 1 – yes, 2 – no or not sure.

Table 1 presents the descriptive statistics of main categorical demographic variables used in the analysis: gender, role, terminal degree level and field of terminal degree (STEM/non-STEM).

Table 1

Descriptive Statistics of The Main Categorical Demographic Variables

Variable	Frequency	Valid %
Gender		
Woman	118	53.2
Man	93	41.9
Non-binary, Agender, Gender fluid, Gender queer, prefer not to answer	11	5.0
Role		
Faculty	98	44.1
Administrative staff member	124	55.9
Terminal degree		
Bachelor's	39	17.6

Variable	Frequency	Valid %
Master's	62	27.9
Doctorate	104	46.8
Professional	6	2.7
Other	11	5.0
Field of degree		
STEM	58	26.1
Non-STEM	164	73.9

Table 2 shows the descriptive statistics of the main study constructs: Technophobia, Technology Leadership (TL) in HE and Intention to Use (ITU) AI-based EAS at HEIs. In analysis, TL in HE has been divided into five sub-scales (Leader Equity and Citizenship Advocate, Leader Visionary Planner, Leader Empowering Leader, Leader Systems Designer, Leader Connected Learner) due to multidimensionality of the construct, as well as potentially different results for each of the sub-scales of the construct.

Table 2

Descriptive Statistics of The Main Continuous Study Constructs

Variable	Min	Max	Mean	SD
Technophobia	1	4.29	2.15	0.83
Technology Leadership in HE	1	5	3.47	1.02
Leader Equity and Citizenship Advocate	1	5	3.61	1.08
Leader Visionary Planner	1	5	3.22	1.24
Empowering Leader	1	5	3.74	1.02
Leader Systems Designer	1	5	3.47	1.15
Leader Connected Learner	1	5	3.32	1.22
Intention to Use AI-based EAS at HEIs	1	5	3.37	1.29
Age	22	73	45.84	11.35

Statistical Analysis

This study used a quantitative study design by testing the previously empirically tested and validated measures of Technophobia, Technology Leadership (TL) in Higher Education (HE) and Intention to Use (ITU) AI-based tools in different countries (China, India, Singapore, US) and industries. Within this study I applied and tested these measures and their relationships in the HE context in the US. The current study design and statistical analyses are aiming at evaluating the potential effect of Technophobia on ITU and Technology Leadership (TL) on ITU in a specific HEI in the southeast of the United States. Statistical methods used in the analysis included: a one-tailed **correlation analysis** for primary constructs: Technophobia, Technology Leadership (TL) in HE and Intention to Use Artificial Intelligence (ITU) AI-based Early Alert System (EAS) at HEIs, as well as correlation analysis between the main study constructs and additional control variables of age, gender, role (faculty vs. administrative staff), terminal degree level and the field of the terminal degree (STEM/non-STEM). Lastly, I conducted an ordinary least squares (OLS) **regression analysis** to understand predictive relationships of the main study constructs, identify significance of the *p*-value, quantify the strength of relationships between the main study constructs and control variables, and control for confounding factors, and assess model fit (Cohen et al., 2013). Regression analysis is a valuable statistical tool for quantitatively examining the relationships between predictor variables (Technophobia and Technology Leadership in HE) and an outcome variable (Intention to Use AI-based EAS at HEIs) in a systematic manner. It helps to better understand the factors influencing the adoption of emerging technologies like AI-based tools in specific contexts, such as higher education. Details of the study statistical analyses and results are described in Chapter 4.

Table 3

Factor Loadings and Reliability for Measured Constructs

Scale and Individual item measures	Loading	Alpha
Technophobia		0.82
I am fearful that someone is using AI-based technologies to watch and listen to everything that I do	0.63	
I am terrified that AI-based technologies will change the way we live, communicate, love, and even judge others	0.79	
I am afraid of new AI-based technologies because one day it will make us (humans) obsolete	0.79	
I am fearful that new AI-based technologies will someday take over my job	0.66	
I am afraid of new AI-based technologies because if something goes wrong with it (if it stopped working for some reason) we will go back to the Stone Age	0.57	
I am afraid of new AI-based technologies because they may interfere with my life emotionally, physically, and psychologically	0.72	
I am fearful that robots may take over the world	0.72	
Technology Leadership (TL) in Higher Education (HE)		
Leader as an Equity and Citizenship Advocate		0.87
My leader ensures that all students have faculty who can use technology actively	0.82	

Scale and Individual item measures	Loading	Alpha
My leader ensures equality of technology access for all students	0.85	
My leader models digital citizenship (the ability to navigate digital environment in safe and responsible way and to actively and respectfully engage in digital spaces) in using technology	0.87	
My leader guides online behaviors regarding safe, ethical, and legal use of technology	0.86	
Leader as a Visionary Planner		0.93
My leader encourages all members to develop a common vision for technology usage	0.76	
My leader designs strategic technology plans	0.93	
My leader evaluates the progress and effect of technology plans	0.95	
My leader gathers input from members to continually improve technology plans	0.89	
My leader shares resources, lessons, and practices of technology usage with members	0.86	
Leader as an Empowering Leader		0.89
My leader empowers members' technology leadership skills and professional learning	0.90	
My leader builds the members' confidence to use technology in practice	0.91	
My leader inspires a culture of innovation and collaboration	0.84	

Scale and Individual item measures	Loading	Alpha
My leader supports members in using technology to meet students' diverse needs	0.86	
My leader provides technology-enabled assessments with feedback on student learning progress in real time	0.69	
Leader as a Systems Designer		0.86
My leader leads technical teams to construct technology infrastructure and systems	0.82	
My leader provides sufficient technology resources for all departments and members	0.81	
My leader guides members to protect data privacy and data security	0.85	
My leader builds internal and external partnerships to connect various digital platforms and improve operations	0.89	
Leader as a Connected Learner		0.91
My leader sets technology goals concerning professional learning for themselves and others	0.91	
My leader regularly participates in and organizes online professional learning activities or communities	0.80	
My leader regularly makes reflections on technology usage for professional growth	0.93	
My leader develops the skills needed to navigate change, and promote a mindset of continuous technology-enhanced professional learning	0.89	

Scale and Individual item measures	Loading	Alpha
Intention to Use Artificial Intelligence (AI)-based Early Alert System (EAS) at HEIs		0.88
I expect that I would use Artificial Intelligence (AI)-based Early Alert System (EAS) tool in the future	0.94	
I plan to use AI-based EAS tool in the future	0.94	

First, the reliability value for the Technophobia items was $\alpha = 0.82$, which aligns with past studies such as Khasawneh and Bellamy (2014) at $\alpha = 0.90$, and Khasawneh (2015, 2018) at $\alpha = 0.90$. This suggests the Technophobia scale's reliability in the HE context is consistent with other organizational settings. Second, reliability values for five separate sub-scales of Technology Leadership (TL) in HE have been estimated. The TL sub-scales include: Leader Equity and Citizenship Advocate, Visionary Planner, Empowering Leader, Systems Designer and Connected Learner. The reliability value for the Equity and Citizenship Advocate was $\alpha = 0.87$, demonstrating its reliability in the HE context (for reference, Yuting et al. (2022) reported $\alpha = 0.88$). The reliability value for the Visionary Planner was $\alpha = 0.93$, indicating its reliability in the HE context, that is slightly higher than Yuting et al.'s (2022) $\alpha = 0.85$. The Technology Leader Empowering Leader had a reliability coefficient of $\alpha = 0.89$, implying its reliability in the HE context, being slightly higher than Yuting et al.'s (2022) $\alpha = 0.84$. The Technology Leader Systems Designer sub-scale in the HE context had a reliability coefficient of $\alpha = 0.86$, close to Yuting et al.'s (2022) $\alpha = 0.85$. The Technology Leader Connected Learner sub-scale in the HE context had a reliability coefficient of $\alpha = 0.91$, higher than Yuting et al.'s (2022) $\alpha = 0.83$.

Summary. In this chapter, I outlined the study's purpose, research questions, and rationale for selecting a quantitative methodology. I also discussed various aspects, including the study sample, data collection methodology, measures used in this study with their operational definitions, as well as data cleaning and coding procedures. Additionally, I presented descriptive statistics, factor loadings, and reliability coefficients for the primary study constructs and their items. A brief overview of the statistical methods used was also provided. In the next chapter, I describe the analysis results and their interpretation.

CHAPTER 4

Results

Introduction

The primary purpose of this research was to quantitatively test the influence of Technology Leadership (TL) and Technophobia toward emerging technologies on the intention of faculty and administrative staff to use AI-based Early Alert Systems (EAS) at James Madison University (JMU) in the southeast of the United States This chapter describes the findings from the data analysis and the testing of previously validated instruments for TL and Technophobia within the higher education settings.

Analysis of the Main Study Constructs. In order to determine potential relationships between the main study constructs, I initiated a one-tailed **correlation analysis** for primary constructs: Technophobia, Technology Leadership (TL) in HE that due to multidimensionality of the construct was analyzed as five separate sub-scales of TL (Leader Equity and Citizenship Advocate, Visionary Planner, Empowering Leader, Systems Designer and Connected Learner), and Intention to Use (ITU) AI-based Early Alert System (EAS) at HEIs. Results can be seen in Table 4.

Table 4

Bivariate Correlations Between Main Study Constructs

	Technophobia	Leader Equity and Citizenship Advocate	Leader Visionary Planner	Empowering Leader	Leader Systems Designer	Leader Connected Learner	Intention to Use AI EAS at HEI	Gender	Age	Role	Terminal Degree	Field of degree (STEM/non-STEM)
Technophobia	1											
Leader Equity and Citizenship Advocate	0.179**	1										
Leader Visionary Planner	0.122*	0.697**	1									
Empowering Leader	0.09	0.763**	0.734**	1								
Leader Systems Designer	0.072	0.700**	0.795**	0.774**	1							
Leader Connected Learner	0.111	0.650**	0.783**	0.756**	0.759**	1						
Intention to Use AI EAS	-0.095	-0.19	0.013	0.099	0.021	0.073	1					
Gender	-0.075	0.031	0.071	-0.01	0.068	0.105	0.065	1				
Age	-0.014	-0.102	-0.059	-0.078	-0.01	-0.07	-0.102	-0.051	1			
Role	0.097	0.169**	0.154*	0.156**	0.177**	0.118*	-0.045	-0.173**	-0.061	1		
Terminal degree	-0.046	-0.132*	-0.125*	-0.143*	-0.124*	-0.141*	-0.004	0.094	0.172**	-0.311**	1	-0.192
Field of degree (STEM/non-STEM)	0.127*	0.008	-0.054	-0.05	-0.074	-0.109	-0.134*	-0.312**	0.022	0.318*	-0.192**	1

**. Correlation is significant at the 0.01 level (1-tailed).
*. Correlation is significant at the 0.05 level (1-tailed).

The correlation analysis results indicate that *Technophobia* and Technology Leadership (TL) in HE sub-scale of Leader Equity and Citizenship Advocate (r = 0.179, p = 0.004), Technophobia and TL sub-scale of Leader Visionary Planner (r = 0.122, p = 0.035), as well as Technophobia and Field of Terminal Degree (STEM/non-STEM) (r = 0.127, p = 0.029) have a weak positive linear relationship that is statistically significant.

Moreover, TL in HE sub-scale *Leader Equity and Citizenship Advocate* has a medium to strong linear relationship that is statistically significant with Leader Visionary Planner (r = 0.697, p <0.001), Empowering Leader (r = 0.763, p <0.001), Leader Systems Designer (r = 0.700, p <0.001), and Leader Connected Learner (r = 0.650, p <0.001), as well as Leader Equity and Citizenship Advocate has a weak positive linear relationship that is statistically significant with the variable of Role (faculty vs. administrative staff) (r = 0.169, p = 0.06), and a weak negative statistically significant relationship with the Terminal Degree Level (r = -0.132, p = 0.025).

Furthermore, TL sub-scale *Leader Visionary Planner* has a strong positive linear relationship that is statistically significant with Empowering Leader (r = 0.734, p < 0.001), Leader Systems Designer (r = 0.795, p < 0.001) and Leader Connected Learner (r = 0.783, p <0.001). Also, Leader Visionary Planner has a weak positive linear statistically significant relationship with the variable of Role (r = 0.154, p = 0.011) and a weak negative statistically significant relationship with the Terminal Degree Level (r = -0.125, p = 0.032).

Additionally, TL sub-scale of *Empowering Leader* has a strong linear relationship that is statistically significant with Leader Systems Designer (r = 0.774, p < 0.001) and Leader Connected Learner (r = 0.756, p <0.001), as well as a weak positive statistically significant relationship with the variable of Role (*r* = 0.156, *p* = 0.01) and a weak negative statistically significant relationship with Terminal Degree Level (*r* = -0.143, *p* = 0.017).

Lastly, the TL sub-scale of *Leader Systems Designer* has a strong positive linear relationship that is statistically significant with Leader Connected Learner (*r* = 0.759, *p* <0.001), as well as a weak positive statistically significant relationship with the variable of Role (*r* = 0.177, *p* = 0.004) and a weak negative statistically significant relationship with the Terminal Degree Level (*r* = -0.124, *p* = 0.033). Sub-scale of *Leader Connected Learner* has a weak positive statistically significant relationship with the variable of Role (*r* = 0.118, *p* = 0.04) and a weak negative statistically significant relationship with the Terminal Degree Level (*r* = - 0.141, *p* = 0.018).

The results indicate that in the context of Technology Leadership (TL) within HE, the role of respondents (whether faculty vs. administrative staff) in this study has shown to have a positive and statistically significant, though weak, correlation with all five sub-scales of TL in HE. On the other hand, the level of terminal degree obtained showed a negative, yet also weak, statistically significant relationship with the same TL sub-scales. These findings suggest interesting possibilities for future research related to additional variables that might influence technology adoption in HE settings.

The study found that the only variable with a statistically significant but weak relationship to the dependent variable — Intention to Use AI-based EAS at HEIs — was the field of degree (STEM vs. non-STEM) (*r* = -0.134, *p* = 0.023). This suggests a potential difference in how individuals with STEM degrees and those with non-STEM degrees perceive the intention to use (and potential further use) of AI tools in HE. However, further research is needed to explore this finding in depth.

Lastly, I conducted an ordinary least squares (OLS) **regression analysis** in order to examine how Technophobia and Technology Leadership (TL) in HE predict the Intention to Use (ITU) AI-based EAS at HEIs. I chose regression analysis as a statistical method for this study, because regression helps to quantify the extent to which the predictor variables influence the outcome variable, providing a clearer understanding of their relationships; control for other potential factors that may influence the intention to use EAS that help to isolate the unique effects of TL and Technophobia; as well as help assess the overall effectiveness of the model by evaluating various goodness-of-fit statistics (e.g., R-squared) that indicate how well the model explains the variance (Cohen et al., 2013) in the intention to use AI-based EAS at HEIs.

Table 5

Summary of Model Fitting for Least Squares Regressions

	Added Covariates	R^2	F	p
Model 1	Age, Gender, Role, Level of Education, STEM degree	0.031	1.372	0.236
Model 2	Technophobia	0.038	1.399	0.216
Model 3	TL sub-scales (Leader Equity and Citizenship Advocate; Leader Visionary Planner; Empowering Leader; Leader Systems Designer; Leader Connected Learner)	0.069	1.396	0.177

Note. Dependent variable - Intention to Use AI tool of EAS at HEIs

In the OLS regression analysis (Table 5), I compared the dependent variable of *Intention to Use AI tool of EAS at HEIs* against several models.

The Model 1 shows that 3.1% (R^2 = 0.031) of the variance in the intention to use AI tool of EAS at a specific HEI can be explained by the combined effect of the covariates of Age, Gender, Role, Level of Education, and Field of Education (STEM/non-STEM). The F-value (F = 1.372) suggests that the model might not be a good fit, as usually an F-value larger than 1 in combination with a low *p*-value would be indicative of a better fit. Since the *p*-value (p = 0.236) is greater than the common alpha level of 0.05, suggesting that the covariates in Model 1 do not have a statistically significant combined effect on the dependent variable.

The Model 2 indicates that scores for Technophobia and predictors included in Model 1 explain 3.8% (R^2 = 0.038) of the variance in the intention to use AI tool of EAS at a specific HEI, where the study has been conducted. Similarly, F-value (F = 1.399) is relatively low and does not indicate a strong model fit. Again, the p-value (p = 0.216) is not significant at the 0.05 level, suggesting that technophobia does not have a statistically significant effect on the intention to use AI tool of EAS at a specific HEI.

The Model 3 suggests that the predictors from Models 1 and 2, as well as five TL in HE sub-scales explain 6.9% (R^2 = 0.069) of the variance in the intention to use AI tool of EAS at a specific HEI, which is a slight improvement over the previous models. The F-value (F = 1.396) continues to indicate a lack of strong evidence for the model fit. The p-value (p = 0.177) remains above the 0.05 threshold, indicating that the TL sub-scales collectively do not significantly predict the intention to use AI tool of EAS at a specific HEI.

Overall, none of the models above provide a strong statistical basis for predicting the intention to use AI tool of EAS at a specific HEI based on the variables included, as indicated by the low R^2 values and non-significant *p*-values. These results suggest that other variables not included in these models may be better predictors of the intention to use AI tool of EAS at HEIs, or that the relationships are more complex than can be captured by these models. Further research could explore additional variables or use different modeling approaches to better understand the factors influencing the intention to use AI tools in HE context.

Table 6

Parameter Estimates for Hierarchical Models (n = 222)

Variable	Model 1 Beta (*SE*)	Model 2 Beta (*SE*)	Model 3 Beta (*SE*)
Constant	4.453 (0.709)	4.683 (0.733)	4.118 (0.813)
Age	-0.011 (0.08)	-0.011 (0.08)	-0.010 (0.008)
Gender	0.075 (0.157)	0.071 (0.157)	0.105 (0.158)
Role	0.021 (0.191)	0.035 (0.191)	0.034 (0.194)
Level of Education	-0.015 (0.094)	-0.016 (0.094)	0.000 (0.095)
Field of Education (STEM/non-STEM)	-0.396 (0.217)	-0.374 (0.217)	-0.313 (0.219)
Technophobia		-0.128 (0.104)	-0.112 (0.106)
Leader Equity and Citizenship Advocate			-0.199 (0.132)

Variable	Model 1 Beta (*SE*)	Model 2 Beta (*SE*)	Model 3 Beta (*SE*)
Leader Visionary Planner			-0.083 (0.132)
Leader Empowering Leader			0.353 (0.164)*
Leader Systems Designer			-0.088 (0.145)
Leader Connected Learner			0.086 (0.130)

* $p < 0.05$

Table 6 indicates parameter estimates (β) and their standard errors (*SE*) for three hierarchical models, with each model representing a different level of complexity by adding additional constructs to each new model and measuring the combined effect of a construct/set of constructs on the dependent variable of the study.

Model 1. *Age* ($\beta = -0.011$, *SE* = 0.08) - a negative beta indicates that as age increases, the dependent variable of Intention to use AI tool of EAS at HEIs decreases slightly, although this result is not statistically significant. *Gender* ($\beta = 0.075$, *SE* = 0.157) suggests a small positive relationship with the dependent variable. This could indicate that the gender of the participants may have a slight influence on their intention to use AI tools. *Role* ($\beta = 0.021$, *SE* = 0.191) has a very small positive effect on the dependent variable, however, this result is not significant. *Level of Education* ($\beta = -0.015$, *SE* = 0.094) - similar to age, a higher education level might slightly decrease the intention to use AI tools, but the effect is likely negligible. *Field of Education (STEM/non-STEM)* ($\beta = -0.396$, *SE* = 0.217) has a more substantial negative beta, suggesting that those from a non-STEM field might be less inclined to use AI tools compared to STEM field individuals. It is important to highlight that none of the results in the Model 1 is statistically significant. Thus, all the initial assumptions above have to be tested further.

Model 2. Adding a covariate of Technophobia ($\beta = -0.128$, *SE* = 0.104), the model shows a negative relationship with the dependent variable, indicating that higher levels of technophobia might be associated with a lower intention to use AI tool of EAS at a specific HEI. The same as in the Model 1, in this model the result was statistically non-significant. Further exploration is required to confirm the assumption of influence of Technophobia on Intention to Use AI tool of EAS at HEIs.

Model 3. Adding covariates of five Technology Leadership in HE sub-scales (*Leader Equity and Citizenship Advocate*: $\beta = -0.199$, *SE* = 0.132; *Leader Visionary Planner*: $\beta = -0.083$, *SE* = 0.132; *Empowering Leader*: $\beta = 0.353$, *SE* = 0.164; *Leader Systems Designer*: $\beta = -0.088$, *SE* = 0.145; *Leader Connected Learner*: $\beta = 0.086$, *SE* = 0.130), the coefficients represent the relationship between different technology leadership in HE sub-scales and the intention to use AI tool of EAS at HEIs. The only statistically significant result with positive beta coefficient was found for Empowering Leader sub-scale of TL in HE suggesting that leaders who foster empowerment within their teams are likely to see a higher intention to use AI tool of EAS at a specific HEI, where the study has been conducted.

Lastly, it is important to highlight the remarkable response rate and depth of answers to the open-ended question in the survey labeled "Q32: What else should we know about the intention to use AI-based EAS at JMU?" This question was part of the Intention to Use AI-based EAS at HEI measurement instrument integrated into the study survey (Appendix E). It was surprising to see that 91 out of 222 respondents (41%) gave detailed responses, providing valuable additional qualitative data that was not planned in the initial study design. Therefore, I decided to compile and categorize these responses into themes and codes, which are presented in detail in Appendix F. The main themes can be grouped into three categories:

Theme 1: Concerns about AI tools' adoption in HEI, including codes related to overreliance on technology; equity, inclusion, data privacy, and transparency; ethics; plagiarism issues; bias; lack of AI tools’ regulations; proficiency in AI (faculty vs. students), and legal liability. Theme 2: Suggested actions and changes, with codes such as culture change; appointing responsible staff in HEIs for reviewing AI policies; demonstrating the value of the AI tools; providing training for proper integration; implementing protocols and procedures; teaching responsible AI tools' use to students, and the need for more education on technology and its ethical implications before widespread adoption. Theme 3: Other observations, including codes related to AI tools' use in various areas of HEI (e.g., Student Affairs Residence life); distinction between instructional and non-instructional staff, and the use of AI for safety purposes.

Interestingly, some responses did not directly address the intention to use AI-based EAS at HEI but instead highlighted broader concerns, perceptions, and thoughts about AI tools in higher education in general. This could be attributed to limited opportunities within HEIs to express staff opinions on the topic, including numerous concerns, or a lack of understanding of EAS tools within HEIs, as these tools are not yet widely used in the institution where the study was conducted. Further discussion on these findings is presented in Chapter 5.

Summary. This study was intended to validate instruments assessing Technophobia and Technology Leadership (TL) in Higher Education (HE), and to what extent these constructs influence the Intention to Use AI-based Early Alert System (EAS) at HEIs. Furthermore, the potential impact of other factors—such as age, gender, role within HEI (faculty vs. administrative staff), level of terminal degree, and field of terminal degree (STEM/non-STEM degree backgrounds) — on the primary constructs was explored. Contrary to previous research in different settings, no strong relationships between these constructs and additional variables were identified in the HE context within a specific institution in the southeast of the United States. From statistically significant findings, though of weak strength, it is worth highlighting that an individual's role in HEI (faculty vs. administrative staff), modestly but significantly positively correlates with all five sub-scales of Technology Leadership (TL) in Higher Education (HE). Contrary, the level of terminal degree obtained showed a negative, yet also weak, statistically significant relationship with the TL in HE sub-scales used in the study. The findings also suggest that a potential difference in how individuals with STEM degrees and those with non-STEM degrees might differently perceive the intention to use an AI tool of EAS in the specific HEI (the first group being more receptive to the AI tools' use than the second). However, the relationship was weak and further research is required to explore this potential finding in depth. The most practical finding of this study seems to be the positive statistically significant effect of Empowering Leadership sub-scale of TL in HE suggesting that leaders who foster empowerment within their teams are likely to see a higher intention to use AI tool of EAS at a specific HEI. The final chapter provides a study summary, discussion on findings, implications, study limitations and suggestions for future research, and overall conclusions.

CHAPTER 5

Discussion, Implications, and Conclusions

Introduction

In this study, I investigated the influence of Technology Leadership (TL) in Higher Education (HE) and Technophobia on the Intention to Use AI tool of Early Alert Systems (EAS) at HEIs. As a leadership scholar, I looked into how technology leadership impacts the intention to use AI tools of EAS in HEIs. I specifically focused on how technology leadership in HE settings can shape the attitudes and intentional behaviors of university administrative staff and faculty to use the new AI tools in the future.

The rapid pace of technological developments has reshaped various industries, and Higher Education (HE) is no exception. While established technology adoption theories like the Theory of Reasoned Actions (TRA) and the Theory of Planned Behavior (TPB), as well as technology adoption models such as the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) offer insights, they might be revisited in terms of addressing future-oriented AI technologies, especially in a change-resilient field such as HE and its institutions (HEIs). Reflecting on this technological landscape transformation, Joo et al. (2016) highlighted the rapid growth of new technologies in education since 2010, including digital textbooks, cloud computing, and interactive technologies. These technologies were largely human-controlled. However, since 2022, the technological environment transformed dramatically, introducing tools like ChatGPT – a generative AI (GenAI) tool by OpenAI – followed by other GenAI tools, such as Bard/Gemini by Google, Bing AI/Copilot by Microsoft and Perplexity AI. These tools started to challenge the human control. Alongside, AI-based Early Alert Systems (EAS), though not yet widespread in HEIs, are at early adoption stage led by institutions like Open University in the UK and Georgia State University in the US. Though, a large number of administrators in HEIs across the world remain unfamiliar with AI-based EAS's functionality and potential benefits. Thus, this study contribution was an attempt to develop a model relevant to technologies still in their early adoption phase, where many potential adopters might be unaware of their capabilities. This task appeared to be challenging and requires further theory and methodology building in future research.

The design principles for such technologies as AI-based EAS should be approached with caution. As emphasized by Zawacki-Richter et al. (2019), the integration of educational technology goes beyond technical considerations. It includes pedagogical, ethical, social, cultural, and economic dimensions. As Selwyn (2016) notes, it is a dangerous path to view data and coding as definitive solutions, because education cannot be solely treated as data analysis and algorithms. Haenlein and Kaplan (2019) also caution that while AI systems show substantial capabilities, they require human oversight, as these systems can make mistakes. Aguilar et al. (2014) suggest a careful approach to user interface design, especially when student data is at stake, ensuring maximum flexibility and privacy. Kentaro Toyama in his book “Geek Heresy” (2015) proposes that technology, in essence, magnifies societal conditions – amplifying both the positive and the negative. This viewpoint highlights the importance of critical and careful approach when integrating technology into education.

Furthermore, the investment management firm Goldman Sachs report’s global estimates indicate that generative AI alone could automate the equivalent of 300 million full-time jobs (Kelly, 2023). This potential for significant job loss due to the adoption of AI technologies has been a repeating theme in media and a source of anxiety for societies globally. Echoing this anxiety, Siau (2017) states, that in professions where there are established and set procedures and policies, automation is likely to happen. In his opinion, if anything can be automated, it will be. This forecast is applicable also to administrative tasks in HEIs, as many of their procedures are rule-driven and could be replaced by automation.

However, not all perspectives on this issue are negative. Aoun (2017) suggests that the AI Revolution could free workers from repetitive tasks, opening the way for more creative jobs and tasks and promoting humanistic qualities such as compassion, kindness, understanding, ethicality, fairness, wisdom, areas where machines currently yet cannot match human capability. Also, the World Economic Forum (WEF) projects in the "Future of Jobs Report 2020", a displacement of 85 million jobs and simultaneously the creation of 97 million new ones across 26 countries by 2025 due to AI automation. This suggests that while some jobs might be replaced by automation, at the same time, they could be replaced by newer, more creative jobs. This transition requires societies and HEIs to prepare for a dynamic workplace where humans and AI technologies coexist harmoniously.

Understanding the current capabilities and limitations of AI technologies in HEIs' administrative and teaching tasks is crucial. Popenici and Kerr (2017) caution against being overly optimistic about AI's potential in education, referencing the Chief Architect of IBM's AI supercomputer Watson, Ruchir Puri, who noted, that despite the AI hype, its current limitations are vast, while its actual capabilities remain limited. At the same time, one cannot underestimate the potential development and increasing level of independence of AI tools. Stakeholders should develop accountability measures, governance frameworks and "safety breaks" for the next iterations of AI tools (WSJ Podcasts, Nov 3, 2023).

Summary of the Study

This quantitative study aimed to examine the influence of Technology Leadership (TL) and Technophobia on the Intention to Use AI-based EAS among faculty and administrative staff at James Madison University (JMU) in Virginia, United States.

The main study research questions (RQ) and hypotheses (H) were: **RQ1**: To what extent does Technology Leadership (TL) in Higher Education (HE) influence faculty and administrative staff members' intention to use AI-based Early Alert Systems (EAS)? **RQ2:** To what extent does Technophobia influence faculty and administrative staff members' Intention to use AI-based Early Alert Systems (EAS)? **H1**: Technology Leadership (TL) is expected to have a direct positive effect on the Intention to Use AI-based Early Alert Systems (EAS) by faculty and administrative staff members at Higher Education Institutions (HEIs). **H2**: Technophobia is expected to have a direct negative effect on the Intention to Use AI-based Early Alert Systems (EAS) by faculty and administrative staff members at Higher Education Institutions (HEIs).

The quantitative analysis showed that the Technophobia scale in the Higher Education (HE) setting is as reliable as in other organizational contexts (Khasawneh, 2015; Khasawneh, 2018). Similarly, the sub-scales of the Technology Leadership (TL) in HE instrument (Equity and Citizenship Advocate, Visionary Planner, Empowering Leader, Systems Designer, and Connected Learner) proved reliable and suitable for future use and validation in various HEIs globally. Interestingly, from the OLS regression analysis of TL in HE sub-scales regarding the Intention to Use AI-based EAS at HEI, only the Empowering Leader sub-scale showed statistical significance. This highlights the importance of empowering leadership in the complicated HE landscape suggesting a need for further exploration in future research.

In sum, answers (A) to the study questions are as follows:

RQ1: To what extent does Technology Leadership (TL) in Higher Education (HE) influence faculty and administrative staff members' intention to use AI-based Early Alert Systems (EAS)?

A1: Technology Leadership in HE and Intention to Use AI-based EAS at HEIs have a weak positive linear relationship that is statistically non-significant.

RQ2: To what extent does Technophobia influence faculty and administrative staff members' Intention to use AI-based Early Alert Systems (EAS)?

A2: Technophobia and Intention to Use AI-based EAS at HEIs have a weak negative linear relationship that is statistically non-significant

Thus, *two hypotheses* of the study *have not been supported.*

Discussion about the Findings

Earlier studies have examined technology adoption theories and models from the 1960s-2000s, such as the Theory of Reasoned Actions (TRA), the Theory of Planned Behavior (TPB), the Technology Acceptance Model (TAM) and Unified Theory of Acceptance and Use of Technology (UTAUT), in settings where technologies were tangible, developed and were adopted on a mass scale at a slower pace, and environments were relatively stable. This study showed that the relationship between Technophobia and Technology Leadership in HE does not impact the Intention to Use AI-based EAS at a specific HEI in the southeast of the United States. I assume that predicting adoption of forward-looking technologies in HE might be less predictable with existing common technology adoption theories and models than they were suited for well-established technologies like computers, cell phones and laptops. The findings of this study suggest the need for new frameworks relevant for daily-evolving AI technologies in the dynamic and multi-faceted HE environment. Current models like UTAUT and TAM may need to be re-evaluated and updated in this changing landscape.

Furthermore, the substantial and unexpected qualitative data obtained from responses to the sole open-ended survey question (Appendix F) suggests that discussions about technology leadership during the AI Era in higher education (HE) might be somewhat premature. This could be attributed to the shock stage experienced by HE stakeholders following the introduction of ChatGPT 3.5 in November 2022. The unexpected number of detailed comments related to respondents' concerns about AI tools, not even specifically EAS, within the HE context, indicates that HE stakeholders are currently struggling with understanding the technology and determining how to deal with it in classrooms. It appears that conversations about technology leadership skills may have occurred a few years earlier than HE stakeholders are currently prepared to review and address this concept. Thus, initially collecting qualitative data on the intention to use AI tools in HEIs at the early adoption stage could be more effective than a solely quantitative method. The qualitative approach might help in identifying initial themes and developing new constructs for further testing and validation in this emerging field.

The most practical finding of this study is the positive statistically significant effect of Empowering Leadership sub-scale of Technology Leadership (TL) in HE suggesting that leaders who foster empowerment within their teams are likely to see a higher intention to use AI tool of EAS at a specific HEI. This suggests that regardless of the other variables considered (demographic variables, technophobia, or other technology leadership sub-scales in HE), the ability to empower followers stands out as an important predictor. Thus, HEIs might consider investing in leadership training programs that focus on empowering styles. Training leaders to empower their staff could be a strategic move to facilitate the adoption of AI technologies in higher education. Further, the significance of an empowering leader could reflect a broader cultural shift within HEIs toward valuing autonomy, collaborative decision-making, and a supportive environment as intrinsic motivation for adopting new AI technologies. Lastly, when implementing AI tools, strategies that are consistent with empowering leadership style may be more effective. This could involve engaging users in the decision-making process and providing them with resources and training that enhance their self-efficacy. At the same time, it is important to note that although the empowering leader sub-scale of TL in HE is significant, the overall models used in this study do not explain a large portion of the variance in the intention to use AI tool of EAS at a specific HEI. Additional research could be conducted to identify other factors that may play a role on the intention to use AI tool of EAS at HEIs.

Theoretical and Practical Implications for Technology Leadership in Higher Education

This study adds to the understanding of technology leadership, particularly within higher education context. Many university leaders and stakeholders are unaware of the technology leadership skills, including equity advocacy, visionary planning, empowerment, systems design, and connected learning. These skills emphasize that all educational leaders, regardless of whether their direct tasks involve technology-related questions, must understand AI technologies' evolution and possess modern leadership competencies. While AI technologies naturally have been integrated into our daily lives through platforms like Google Search, Amazon, Netflix, Google Maps and others, many often overlook the AI-based technologies that are behind these platforms. The real challenge is determining how educational stakeholders can utilize AI-based tools effectively, ethically, and without overreliance on them. The question is no longer whether emerging technologies like AI will be a part of our lives, but how we, as educational stakeholders, will coexist and benefit from them.

University leaders have an important role in both overseeing and empowering administrators and faculty, requiring robust and credible assessment mechanisms. Embracing technology leadership is essential for modern university administrators. In essence, these technology leaders must be aware of the various facets where they can effectively lead technological development, adoption and use. When formulating AI technologies and tools' adoption strategies in HE, policymakers should be mindful of the different levels, needs, and feedback of HE leaders, administrators, faculty, students and other educational stakeholders, emphasizing the importance of continuous technology leadership and AI literacy related professional development opportunities.

Furthermore, the increasing pace of technological developments means that higher education institutions cannot afford to be reactive. Instead, they should be proactive, anticipating changes and trends, and incorporating them into their strategic visions and operational plans. This proactive approach to technological leadership ensures that universities remain at the forefront of innovation, delivering education that is both relevant and future-proof (Aoun, 2017).

It is also important for higher education technology leaders to advocate for ethical considerations. AI technologies and tools while powerful, come with human biases and potential for misuse. By aligning their leadership with ethical principles, university leaders can ensure that AI tools' adoption not only advances academic and administrative tasks but also is university mission-responsive, transparent, accountable and equity-minded (Selznick & Titareva, 2022).

In the field of educational technology, different categories of AI tools emerge. Each category has its own set of implications for educational stakeholders. For example, generative AI tools ("dangerous" tools) pose substantial risks and ethical concerns, particularly related to undetectable plagiarism, as their generative nature can lead to academic dishonesty, requiring stakeholders to struggle with the challenge of maintaining academic integrity while utilizing these powerful tools. Contrary, AI-based EAS (labeled "tools with promise") hold significant promise for student retention, and their benefits may outweigh the risks. EAS serve as valuable assistants to human administrators, providing additional feedback and identifying students at risk of dropping out, without threatening extensive job cuts or requiring major behavioral change among users. The weak relationship between technology leadership (TL) in higher education and intention to adopt AI-based EAS within this study may be influenced by the specific context of “less dangerous tools” like EAS. Exploring the influence of more "dangerous" AI tools (e.g., teaching robots replacing faculty) that may stimulate stronger feelings of technophobia on adoption intentions, as well as the need for stronger involvement of technology leaders on the adoption of such tools, requires further investigation. Understanding the balance between risks and promise of diverse AI tools is essential for informed decision-making in new technology adoption in HE settings. This nuanced perspective encourages further exploration into the relationships between diverse factors influencing adoption of AI tools in HEIs and intentions to use such tools.

Additionally, the construct of " intention to use" implies that the adoption of a technology is a choice, where users can decide whether to adopt and use or not. However, future studies could explore the possibility that technology leadership (TL) in higher education and technophobia may have stronger effects in situations where people do not have the choice to use a technology. In such cases, internal HE stakeholders are informed that a change will take place, rather than having the voluntary option to adopt or reject the technology. The lack of choice in these situations may result in stronger responses from users. This factor of voluntary versus mandatory adoption and use could have important implications for theory development and future research in the field of technology adoption in HE. Looking into scenarios where people do not have a choice in adopting a technology may lead to a more nuanced understanding of the factors influencing the technology adoption. By exploring the distinction between voluntary and involuntary adoption, researchers can gain valuable insights that can inform and refine existing technology adoption theories and models in relationship to AI-based tools. This perspective can contribute to the advancement of the field and help educational stakeholders make more informed decisions regarding the implementation of emerging technologies.

Lastly, as leadership scholars, we must consider the relevance and applicability of dominant technology adoption theories for the adoption of AI-based technologies and tools, particularly in the context of higher education. Just as the "Great Man" leadership concept was widely used for decades before being critically evaluated and regarded less relevant for modern times, we must approach the use of established technology adoption theories and models, with a similar level of scrutiny. The question we must ask ourselves is: Are these theories, which were developed for the technologies of previous generations, truly suitable for measuring the intention to use or the actual use of AI-based technologies and tools in the field of AI in Education (AIEd)? The nature of AI-based technologies and tools, and the future-looking intention to use them, may require a different set of theories and adoption models. These emerging technologies and their potential unintended consequences are not yet fully known to us as a society, which poses a unique challenge in measuring their adoption and use. We must respect the established technology adoption theories, but also critically evaluate their relevance and applicability in the new technological context. What would be the best ways to measure something that is still evolving and whose long-term impacts are not yet fully understood? This critical examination of the existing theories and the exploration of alternative approaches could lead to valuable insights and the development of more appropriate theories and models for measuring the adoption of AI-based technologies in the field of higher education. By doing so, we can ensure that our research and decision-making processes are aligned with the unique characteristics and challenges presented by the rapidly advancing AI discipline and technologies.

To sum up, technology leadership in higher education is not only about understanding and implementing the latest technological tools. It is about developing a vision for the future, based on ethics and equity, and working collaboratively toward that vision. In the rapidly evolving landscape of AI, higher education leaders have the responsibility and the opportunity to shape the direction in which we move, ensuring the best outcomes for all stakeholders.

Limitations and Opportunities for the Future Studies

This study, like all research projects, comes with its limitations as described below. They can be viewed as limitations, as well as opportunities for future research.

General Study Limitations. One of the main limitations of this study is related to its quantitative nature, gathering data from only one university in the southeast of the United States. Such a limited scope does not permit broad generalizations across other HEIs both nationally and internationally. To truly validate these findings, additional empirical studies are required, including diverse contexts, larger sample sizes, and diverse populations.

Moreover, the dependent variable of this study "Intention to Use AI-based EAS at HEIs," could be substituted with other variables. Exploring how Technology Leadership (TL) in HE and Technophobia impact these alternative variables, as well as identifying potential moderating and mediating variables, would be beneficial. Evaluating other predictors that influence the intention to use established AI tools, like ChatGPT, Microsoft Copilot or Google Gemini, which may soon be mainstream in educational contexts, would also be beneficial for scientific community, practitioners and policy makers.

Lastly, clarity is required between terms like "digital leadership" and "technology leadership in the digital age." The urgency of this clarity becomes evident when we consider the rapid technological changes HEIs are undergoing. While there is a solid amount of leadership research in sectors such as management and the military, a gap exists when it comes to leadership in higher education, especially during the times of increasing digital transformations across university campuses (Ehlers, 2020).

The Study Instrument's Limitations. The present study's instrument, which includes measures of Technophobia, Technology Leadership in Higher Education and Intention to Use AI-based Early Alert Systems (EAS) at HEIs, as well as demographic variables, has several limitations described below.

Ambiguity in leadership roles within higher education (HE). Survey responses indicated confusion about who constitutes a "leader" in the HE context. Respondents questioned whether their Academic Unit Head (AUH), Dean, Provost, or the overarching James Madison University (JMU) held this role. Furthermore, there was a perception among respondents that immediate supervisors lacked authority over technology-related decisions, highlighting a gap between leadership roles and technology governance within HE. Future studies could specify what level leaders respondents are evaluating - direct supervisors, IT department colleagues or top leadership of university - when assessing technology leadership skills.

Difference in survey applicability for faculty and administrative staff in HE. The survey's relevance varied between administrative and faculty respondents, suggesting the survey instrument may not be universally applicable across these roles. One respondent noted that many questions were not relevant to their non-instructional academic unit but still commented on broader leadership attitudes toward technology within the institution. Future studies could distinguish and use different measurement instruments for faculty and administrative staff taking into consideration specifics of each role and their leaders' responsibilities.

Lack of visuals of new AI-based tool of EAS at HEIs. Several participants felt the survey could benefit from visual aids, especially given its focus on technologies not yet common in HE, like AI-based Early Alert Systems (EAS). The absence of descriptive visuals led to requests for more explanations about the technology interface and its potential benefits. Further studies related to future AI tools' adoption could describe the essence of the technology and its benefits, as well as add some visuals.

Absence of "not applicable" option in Technology Leadership (TL) in HE instrument. Some respondents highlighted the lack of a "not applicable" option in TL questions, noting that their immediate leader was not responsible for many of the technology-related tasks mentioned. This shows a disconnect between the survey's assumptions and the diverse roles that different leaders occupy within a university setting. Adding this option to the existing tool of TL in HE (Appendix E), could be an option for future attempts to test the tool in different HEIs globally.

Lack of clear definition of "technology plans" within HE context. The survey was critiqued by some respondents for not providing enough context about technology plans as part of items operationalizing the TL in HE sub-scale of Visionary Planner specific to faculty and staff roles within HE. This left some respondents unable to make informed decisions. This valuable comment could be clarified in the future use of the TL measurement scale and made clearer to HE stakeholders what the sub-scale of Visionary Planner implies by technology plans.

Preconceived assumptions about Technophobia. Finally, the survey's questions around "technophobia" were perceived by some respondents as leading and potentially biasing. Respondents expressed that the term "fearful" or “terrified” were too strong, suggesting preconceived notions about attitudes toward AI and technology. This could introduce a priming effect, possibly influencing how participants responded to questions about understanding the technology.

Future research should focus on developing comprehensive frameworks that guide the ethical integration and use of AI tools in higher education settings. This could include exploring the long-term impacts of AI tools on educational policies, teaching methodologies, student learning outcomes, enhancement or replacement of routine administrative tasks with reskilling trainings developed and available for the non-instructional staff at HEIs. Additionally, there is a need to expand theory to incorporate the dynamic interplay between technology and human elements in higher education, with focus on how AI tools’ adoption influence decision-making processes, organizational culture, and equity in educational opportunities. Further investigation into the relationship between technology leadership and student success, as well as faculty and administrative staff development in the context of AI field and tools development, could provide valuable insights. Lastly, by advancing research in these areas, we can better understand and utilize the transformative potential of AI tools in shaping the future of higher education.

Conclusions

While technology leadership in higher education presents its own set of challenges and has received limited scrutiny (Keengwe et al., 2009; Yuting et al., 2022), the role of technology leaders has evolved. Rather than just overseeing the institution and managing everyday administrative tasks, today's technology leaders undertake multifunctional roles. They influence stakeholders in various ways, including developing a collective technology vision and developing technology plans, promoting innovation in different areas of HE, including with the help of technology, and offering digital resources together with digital training opportunities (Chua & Chua, 2017; Webster, 2017; Yuting et al., 2022). According to Bates et al. (2020), AI remains a "sleeping giant." The technologies are going to evolve with unprecedented speed. Additionally, the most transformative AI applications are likely to emerge not from the perspective of HEIs' users but rather from corporate business entities having vast datasets, opening the way for scalable AI solutions, including in higher education. In this light, Popenici and Kerr (2017) suggest that universities reevaluate their role, pedagogical models, and relationship with AI solutions and their providers.

Discussions about AI and leadership in higher education need to extend beyond the technology as the central aspect. Issues like equity, inclusion, data privacy, and ethics must be addressed, along with governance frameworks. For instance, when AI tools like Early Alert Systems (EAS) predict student performance, administrators and faculty must consider fairness and the potential psychological impact on students who may be negatively affected by automated decisions. It is important to note that these AI tools are created by humans, who may unintentionally program their own biases. As highlighted by this study survey respondent, such biases can lead to negative academic and emotional outcomes for students, including lowered performance and feeling of marginalization.

For a long-term view, it is essential to consider more than just the technical progress of AI tools or efficiency gains at HEIs. A multi-stakeholder dialogue, involving sectors like business, academia, government, non-profits and think tanks, is very important for utilizing AI technologies in a way that is both efficient and inclusive in HE context. Emphasis should also be on human-driven final decisions rather than algorithmic ones. Additionally, developing guidelines and addressing ethical issues are key to ensuring a safe collaboration between HE stakeholders and AI technology and its developers.

Whether AI technologies is a gift or curse to society and education, one is certain – it is here to stay and will only evolve and become more complex by producing more sophisticated outputs over time (Cribben & Zeinali, 2023). It is essential that human decision-makers retain the ultimate authority, when AI is solely the technology (Chen, 2022), and decision-makers at HEIs stay managers and leaders with comprehensive technology leadership training and outlook on this technology (Bagranoff & Bryant, 2020), instead of relying on the technology suggesting final decisions.

HEIs' leadership should envision the future without being attached to the past experiences when assessing AI's potential. Diamandis and Kotler (2020) state, we often approach risks with a linear mindset, attempting to use past solutions for future challenges. Leaders and policy makers need an agile, open, and innovative mindset in addressing AI opportunities and risks. Microsoft founder, Bill Gates (2023) states, the humanity is in the early stages of AI technologies' development and potential. Its current limitations will soon be gone and the tools will become more powerful. As leadership practitioners and scholars, our foresight should anticipate this growing power of AI tools in higher education. Our primary focus should remain on the growth and well-being of students, and enhancement of work of faculty and administrators. When integrating technology, it is crucial to do so responsibly, ensuring that technology serves as an assistant rather than replacement.

If higher education leaders and other HE stakeholders do not fully address the key points and concerns mentioned above, future implications could include a lack of effective, ethical integration and use of AI technologies in HEIs, potential job losses due to automation, and challenges in adapting to rapidly changing technological landscapes. This could lead to universities falling behind in innovation, insufficiently preparing students for future job markets, and potentially harmful impacts on educational equity and data privacy. It is essential for leaders to be proactive, emphasizing ethical considerations, continuous technology leadership, and AI literacy in their strategies.

Appendix A

Author Approvals for Measurement Instrument Use

Instrument 1: Technophobia: Artificial Intelligence (AI) in HEIs (adapted for the needs of the study from the publicly available tool in in Khasawneh, 2015, p. 145; Khasawneh, 2018)

From: Titareva, Tatjana Nikolajevna - titaretn <titaretn@jmu.edu>

Date: Wednesday, June 14, 2023 at 5:17 PM

To: odaikhasawneh84@gmail.com <odaikhasawneh84@gmail.com>

Cc: Selznick, Ben - selznibs <selznibs@jmu.edu>

Subject: Request for Permission to Adopt and Use Your Measurement Instrument of Technophobia on Technology Adoption in PhD Dissertation

Dear Mr. Khasawneh,

I hope this email finds you well. My name is Tatjana Titareva, and I am currently pursuing a PhD in Strategic Leadership Studies at James Madison University, Virginia, USA. I am writing to seek your permission to adopt and utilize your measurement instrument of Technophobia on Technology Adoption questionnaire (p. 144 of your dissertation), in my PhD dissertation research.

I have carefully reviewed your work on the measurement of Technophobia on Technology Adoption, and I believe that your instrument aligns perfectly with the objectives of my research. My dissertation focuses on investigating the *influence of technology leadership on the intention to use AI-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs).* Your measurement instrument would be invaluable in gathering data related to the technophobia levels of participants in my study.

I assure you that the data collected using your measurement instrument will be used solely for academic research purposes and will be treated with the confidentiality. Proper citation and acknowledgment will be given to you and your work throughout my dissertation.

If you grant me permission to use your measurement instrument, I will ensure that all necessary ethical guidelines and protocols are strictly followed during the data collection and analysis process. Furthermore, I would be more than willing to share the final results of my research with you upon its completion.

I kindly request your prompt response regarding this matter, as I have defended my proposal and am preparing for the data collection stage. Should you require any additional information or have any concerns, please do not hesitate to contact me. I greatly appreciate your consideration and look forward to your favorable response.

Thank you for your time and consideration.

Kind regards,

Tatjana Titareva

Doctoral Assistant at X-Labs / Research & Scholarship

Ph.D. student in Strategic Leadership at School of Strategic Leadership Studies (SSLS)

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From: Odai Khasawneh <odaikhasawneh84@gmail.com>

Date: Wednesday, June 14, 2023 at 6:27 PM

To: Titareva, Tatjana Nikolajevna - titaretn <titaretn@jmu.edu>

Subject: Re: Request for Permission to Adopt and Use Your Measurement Instrument of Technophobia on Technology Adoption in PhD Dissertation

CAUTION: This email originated from outside of JMU. Do not click links or open attachments unless you recognize the sender and know the content is safe.

Hello Tatjana,

Thanks for reaching out to me about using my scale in your dissertation. You have my permission to use my scale in your dissertation. Also, I would love to read the findings of your research once you are done. Feel free to reach out during the process if you have any questions or concerns as I would be happy to provide help and support in your academic endeavors

I attached an article that I think you might find interesting since it contains the scale and how I define Technophobia.

Regards

Odai

Instrument 2: Technology Leadership (Skills) in Higher Education (adopted for the needs of the study from the publicly available tool in Yuting et al., 2022, p. 10303).

From: Titareva, Tatjana Nikolajevna - titaretn <titaretn@jmu.edu>

Date: Wednesday, June 14, 2023 at 5:39 PM

To: 17220218@siswa.um.edu.my <17220218@siswa.um.edu.my>, zhangyuting@um.edu.my <zhangyuting@um.edu.my>, donnieadams@um.edu.my <donnieadams@um.edu.my>, kennycheah@um.edu.my <kennycheah@um.edu.my>

Cc: Selznick, Ben - selznibs <selznibs@jmu.edu>

Subject: Request for Permission to Adopt and Use Your Measurement Instrument of Technology Leadership in HE in PhD Dissertation

Dear Dr. Zhang Yuting, Dr. Donnie Adams & Dr. Kenny Cheah Soon Lee,

I hope this email finds you well. My name is Tatjana Titareva, and I am currently pursuing a PhD in Strategic Leadership Studies at James Madison University, Virginia, USA. I am writing to seek your permission to adopt and utilize your measurement instrument of Technology Leadership in Higher Education (HE) (p. 10303 of your empirical study), in my PhD dissertation research.

I have carefully reviewed your work, and I believe that your instrument aligns perfectly with the objectives of my research. My dissertation focuses on investigating the *influence of technology leadership on the intention to use AI-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs).* Your measurement instrument would be invaluable in gathering data related to the perceptions of technology leadership skills of participants' leaders in my study.

I assure you that the data collected using your measurement instrument will be used solely for academic research purposes and will be treated with confidentiality. Proper citation and acknowledgment will be given to you and your work throughout my dissertation.

If you grant me permission to use your measurement instrument, I will ensure that all necessary ethical guidelines and protocols are strictly followed during the data collection and analysis process. Furthermore, I would be more than willing to share the final results of my research with you upon its completion.

I kindly request your prompt response regarding this matter, as I have defended my proposal and am preparing for the data collection stage. Should you require any additional information or have any concerns, please do not hesitate to contact me. I greatly appreciate your consideration and look forward to your favorable response.

Thank you for your time and consideration.

Kind regards,

Tatjana Titareva

Doctoral Assistant at X-Labs / Research & Scholarship

Ph.D. student in Strategic Leadership at School of Strategic Leadership Studies (SSLS)

James Madison University (JMU)

Harrisonburg, USA / Riga, LATVIA

E-mail: titaretn@jmu.edu

LinkedIn: https://www.linkedin.com/in/tatyanatitareva/

From: Donnie Adams <donnieadams@um.edu.my>

Date: Thursday, June 15, 2023 at 10:40 AM

To: Titareva, Tatjana Nikolajevna - titaretn <titaretn@jmu.edu>

Subject: Re: Request for Permission to Adopt and Use Your Measurement Instrument of Technology Leadership in HE in PhD Dissertation

CAUTION: This email originated from outside of JMU. Do not click links or open attachments unless you recognize the sender and know the content is safe.

Dear Tatjana,

Greetings from Malaysia. Thank you for your interest in our work. You have our consent to adopt and utilize our instrument of measuring Technology Leadership in Higher Education in your research.

We wish you all the best in your studies.

Cheers,

Donnie

Appendix B

IRB Study Approval Letter

JAMES MADISON UNIVERSITY

NOTICE OF EXEMPT APPROVAL

DATE:	June 14, 2023
TO:	Tatjana Titareva, Strategic Leadership Studies Benjamin Selznick, Strategic Leadership Studies
FROM:	Lindsey Harvell-Bowman, Associate Professor, IRB Panel
PROTOCOL TITLE:	Technology Leadership Influence on Intention to Use AI-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs)
FUNDING SOURCE:	NASPA Foundation 2023 Channing Briggs Small Research Grant
PROTOCOL NUMBER:	23-4186

The request for an exempt determination for the above-referenced study has been approved.The study was determined to be research that is exempt from Institutional Review Board (IRB) review under 45 CFR 46.104 Category 2. The project as described in the application may proceed without further oversight.

Exempting an activity from review does not absolve you from ensuring that the welfare of the subjects participating in the research is protected and that methods used and information provided to gain subject consent are appropriate to the activity. You are reminded that any changes in your protocol that affects human subjects must be submitted to the IRB to determine if review and approval will be required *before* implementing new procedures.

Please direct any questions about the IRB's actions on this project to the IRB Chair:

Dr. Lindsey Harvell-Bowman
harve2la@jmu.edu
(540) 568-2611

Lindsey Harvell-Bowman

OFFICE OF RESEARCH INTEGRITY | MSC 5738
HARRISONBURG, VA 22807
540.568.7025 PHONE

Appendix C

Survey Recruitment E-mail

Subject: JMU Phd student collecting data for dissertation related to Technology Leadership and Intention to Use AI-based tools in HEIs

Dear Respondent,

My name is Tatjana Titareva. I am a Phd student at JMU School of Strategic Leadership Studies (SSLS). Currently, I am writing dissertation titled "Technology Leadership Influence on Intention to Use Artificial Intelligence (AI)-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs)" which is also supported by NASPA Foundation Channing Briggs Small Research Grant that is interested in empirical research in technology leadership influence on the AI tools' adoption in HEIs context.

If you are a member of the **administrative staff or tenured or adjunct faculty at JMU**, I would appreciate your input to the survey below. The survey takes approximately 15 minutes to fill in.

This anonymous survey (unless respondents voluntarily wish to identify themselves at the end of the survey in order to participate in a focus group) results will be collected in the period: June – September 2023 and analyzed: October – December 2023. The anonymous data in an aggregated format (without disclosing individual responses) will be presented at Phd defense at SSLS and NASPA conference.

I envision minimal direct or indirect risk to the survey respondents.

Feel free to withdraw from the survey at any point without any penalty.

Link to the online survey: https://jmu.questionpro.com/t/AXm5bZxjVl

Thank you very much for your help!

Useful definition: Early Alert Systems (EAS) are AI-based machine learning algorithms that help to recognize, classify and predict the student's achievement in advance (Aybek & Okur, 2019), as well as to model student profiles to make predictions about future performance. EAS help to detect at-risk students in their first year or to predict the attrition of undergraduate students (Zawacki-Richter et al., 2019).

In case of additional questions or technical challenges, feel free to contact me at: titaretn@jmu.edu or message at xxx.

Kind regards,

Tatjana Titareva

P.S. IRB approval nr. 23-4186

Appendix D

Survey Participant Consent Form

Dear Respondent,

My name is Tatjana Titareva. I am a Phd student at JMU School of Strategic Leadership Studies (SSLS). Currently, I am writing my dissertation titled “Technology Leadership Influence on Intention to Use Artificial Intelligence (AI)-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs)”.

If you are a member of administrative staff and/or tenured or adjunct faculty at JMU, I would highly appreciate your input to the survey below. The survey takes approximately 15 minutes to fill in.

Identification of Investigators & Purpose of Study

You are being asked to participate in a research study conducted by Phd student Tatjana Titareva and supervised by Dr. Benjamin Selznick and Dr. Paul Mabrey from James Madison University. The main purpose of this study is to test the potential influence of Technophobia and Technology Leadership (TL) on Intention to Use AI-based Early Alert Systems (EAS) in Higher Education Institutions (HEIs).

This study will contribute to the researcher’s – Tatjana Titareva - completion of her doctoral dissertation and NASPA Foundation grant.

Here are the specifics of the survey process, the amount of time it will take, how your information will be kept confidential, the chance to withdraw, and the contact details of the researchers and IRB. Once you reach the end of this page and click 'next' to continue with the survey, you give your consent.

Research Procedures

The first stage of this study consists of an online survey that will be administered to individual participants through QuestionPro. You will be asked to provide answers to a series of questions related to Technology Leadership (TL), Technophobia of emerging technologies (like AI-based tools) and Intention to Use AI-based Early Alert Systems (EAS) in higher education institutions (HEIs).

Time Required

Participation in this study will require about 8 - 10 minutes of your time.

The investigator does not perceive more than minimal risks from your involvement in this study (that is, no risks beyond the risks associated with everyday life).

Confidentiality

The results of this research will be presented at Tatjana Titareva's Phd dissertation defense, as well as a poster at NASPA conference. While individual responses are anonymously obtained and recorded online through the QuestionPro software, data is kept in the strictest confidence. No identifiable responses will be presented in the final form of this study. All data will be stored in a secure location only accessible to the researcher. The researcher retains the right to use and publish non-identifiable data. At the end of the study, all records will be destroyed. Final aggregate results will be made available to participants upon request.

Participation & Withdrawal

Your participation is entirely voluntary. You are free to choose not to participate. Should you choose to participate, you can withdraw at any time without consequences of any kind. However, once your responses have been submitted and anonymously recorded you will not be able to withdraw from the study.

Questions about the Study

If you have questions or concerns during the time of your participation in this study, or after its completion or you would like to receive a copy of the final aggregate results of this study, please contact:

Tatjana Titareva	Dr. Benjamin Selznick
School of Strategic Leadership Studies	School of Strategic Leadership Studies
James Madison University	James Madison University
titaretn@jmu.edu	selznibs@jmu.edu

Questions about Your Rights as a Research Subject

Dr. Lindsey Harvell-Bowman

Chair, Institutional Review Board

James Madison University

(540) 568-2611

harve2la@jmu.edu

Giving of Consent

I have been given the opportunity to ask questions about this study. I have read this consent and I understand what is being requested of me as a participant in this study. I certify that I am at least 18 years of age. By completing and submitting this anonymous survey, I am consenting to participate in this research.

This study has been approved by the IRB, protocol #23-4186.

Appendix E

Study Survey

Survey Title: Technology Leadership Influence on Intention to Use AI-based Early Alert Systems (EAS) at Higher Education Institutions (HEIs)

For survey parts 1, 2 and 3, Likert scale from 1 to 5 (*1 – disagree, 2 – slightly disagree, 3 – neither agree/disagree, 4 – slightly agree, 5 – agree*) was used to receive quantitative feedback from respondents.

Survey Part 1

Technophobia: Artificial Intelligence (AI) in HEIs

Q1: I am fearful that someone is using AI-based technologies to watch and listen to everything that I do

Q2: I am terrified that AI-based technologies will change the way we live, communicate, love, and even judge others

Q3: I am afraid of new AI-based technologies because one day it will make us (humans) obsolete

Q4: I am fearful that new AI-based technologies will someday take over my job

Q5: I am afraid of new AI-based technologies because if something goes wrong with it (if it stopped working for some reason) we will go back to the Stone Age

Q6: I am afraid of new AI-based technologies because they may interfere with my life emotionally, physically, and psychologically

Q7: I am fearful that robots may take over the world

"Psychological palate cleanser" 1

A small break. Please choose your favorite ice cream flavor:

Survey Part 2

Technology Leadership (Skills) in Higher Education

Block 1. My Leader as an Equity and Citizenship Advocate

Q8: My leader ensures that all students have faculty who can use technology actively

Q9: My leader ensures equality of technology access for all students

Q10: My leader models digital citizenship (the ability to navigate digital environment in safe and responsible way and to actively and respectfully engage in digital spaces) in using technology

Q11: My leader guides online behaviors regarding safe, ethical, and legal use of technology

Block 2. My Leader as a Visionary Planner

Q12: My leader encourages all members to develop a common vision for technology usage

Q13: My leader designs strategic technology plans

Q14: My leader evaluates the progress and effect of technology plans

Q15: My leader gathers input from members to continually improve technology plans

Q16: My leader shares resources, lessons, and practices of technology usage with members

Block 3. My Leader as an Empowering Leader

Q17: My leader empowers members' technology leadership skills and professional learning

Q18: My leader builds the members' confidence to use technology in practice

Q19: My leader inspires a culture of innovation and collaboration

Q20: My leader supports members in using technology to meet students' diverse needs

Q21: My leader provides technology-enabled assessments with feedback on student learning progress in real time

Block 4. My Leader as a Systems Designer

Q22: My leader leads technical teams to construct technology infrastructure and systems

Q23: My leader provides sufficient technology resources for all departments and members

Q24: My leader guides members to protect data privacy and data security

Q25: My leader builds internal and external partnerships to connect various digital platforms and improve operations

Block 5. My Leader as a Connected Learner

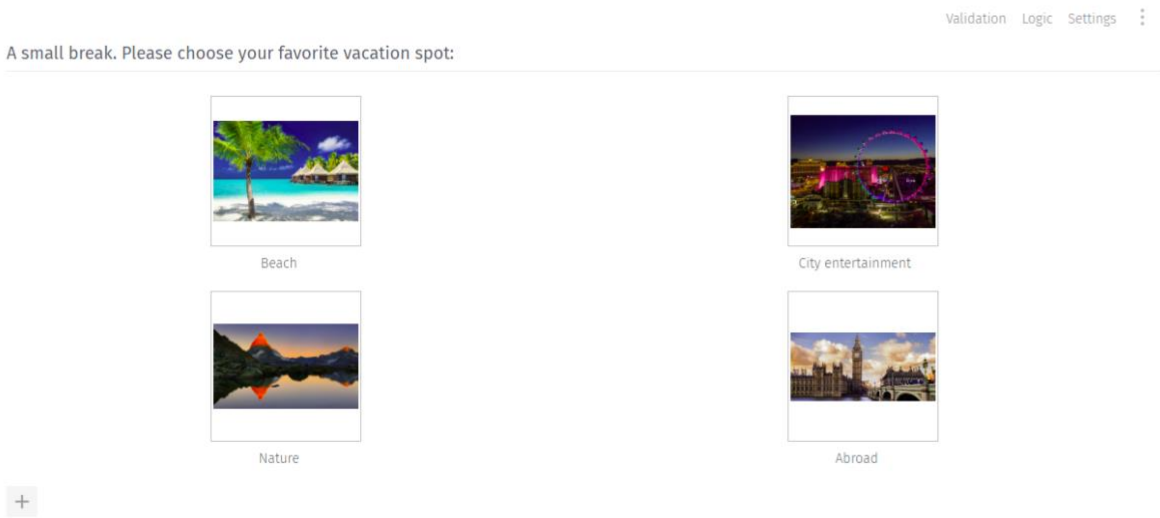
Q26: My leader sets technology goals concerning professional learning for themselves and others

Q27: My leader regularly participates in and organizes online professional learning activities or communities

Q28: My leader regularly makes reflections on technology usage for professional growth

Q29: My leader develops the skills needed to navigate change, and promote a mindset of continuous technology-enhanced professional learning

“Psychological palate cleanser” 2



Survey Part 3

Intention to Use Artificial Intelligence (AI)-based Early Alert System (EAS) at JMU*

*Imagine if in 5 – 10 years JMU is integrating automated Early Alert System (EAS) (in simple terms, a dashboard with predictive analysis of each student’s success in a course/studies)

Q30: I expect that I would use Artificial Intelligence (AI)-based Early Alert System (EAS) tool in the future

Q31: I plan to use AI-based EAS tool in the future

Q32: What else do you think we should know that we haven’t asked you about in relation to the intention to use AI-based EAS at JMU?

Survey Part 4

Demographic Questions

Q33: **Gender**

Which of the following best describes you? *(Select one answer)*

Woman

Man

Non-binary

Agender

Gender fluid

Gender queer

Prefer not to answer

Q34: **Age** What is your Age as of today (in years)?

Q35: **Race**

I identify as: (Select all that apply)

American Indian or Alaska Native

Middle Eastern or North African

Asian or Asian American

Native Hawaiian or Pacific Islander

Black or African American

White

Hispanic, Latinx, or Spanish origin

Another race or ethnicity not listed above

Do not wish to disclose

Q36: **Main role at JMU**

What is your main role at JMU (time dedicated to this role is over 60% an academic year)?

(Select one answer)

Faculty (proceed to Q37)

Administrative staff (proceed to Q38)

Q37: If you are a faculty, which **JMU college do you represent?**

College of Arts and Letters

College of Business

College of Education

College of Health and Behavioral Studies

College of Integrated Science and Engineering

College of Science and Math

College of Visual and Performing Arts

Honors College

Q38: If most of your work at JMU is dedicated to administrative work, **which department do you work for?**

Academic Affairs (proceed to Q41)

Student Affairs (proceed to Q39)

Access and Enrollment Management (proceed to Q41)

Administration and Finance (proceed to Q41)

Advancement (proceed to Q41)

Diversity, Equity and Inclusion (proceed to Q41)

Other (proceed to Q41)

Q39: If you are from JMU Student Affairs (SA), which area of SA do you represent?

Diversity, Equity, Inclusion, and Accessibility

Student Life and Involvement

Health and Well-Being

Career, Experiential Learning, and Transitions

Students Office

Center for Multicultural Student Services

University Unions

Counseling Center

Community Engagement and Volunteer Center

Office of Disability Services

Office of Residence Life

University Health Center

Orientation

Sexual Orientation, Gender Identity and Expression Programming

Office of Student Accountability & Restorative Practices

University Recreation

University Career Center

Office of Student Life

Health Promotion

Other

Q40: How important are the following issues for the future of Student Affairs *(1 - "not at all important," 2 - "slightly important," 3 - "important," 4 - "fairly important," 5 - "very important")*:

Protecting DEIA work

Staff retention

Student wellbeing

AI/Technology Leadership

Promoting sense of belonging

Academic success

Career development

Fraternity/Sorority life

Religious/Spiritual/Secular life

Co-curricular engagement

Residential experiences

Q41: **Terminal degree level**

What is your terminal degree level (completed)? *(Select one answer)*

Bachelor’s

Master’s

Doctorate

Professional

Other

Q42: **Field of terminal degree**

What is the field of your terminal degree (completed)? *(Select one answer)*

Arts (e.g., Fine/Applied Arts, Drama/Theater, Music, Journalism, Speech, Communications, Media Studies)

Humanities (e.g., Classics, English Language/Literature, Foreign Language, History, Philosophy)

Social Science (e.g., Anthropology, Economics, Ethnic Studies, Geography, Political Science, Psychology, Sociology, Social Work, Women’s/Gender Studies, Cultural Studies)

Religion or Theology

Biological Science (e.g., Biology, Botany, Biochemistry, Environmental Science, Marine Biology, Microbiology, Zoology)

Computer Science

Physical Science (e.g., Astronomy, Chemistry, Earth Science, Physics)

Mathematics/Statistics

Engineering (e.g., Aeronautical, Civil, Chemical, Computer Science, Electrical, Industrial, Mechanical)

Health Professional (e.g., Health Technology, Nursing, Medicine, Pharmacy, Therapy)

Business (e.g., Accounting, Finance, Business Administration, Marketing, Management)

Education (e.g., Elementary Education, Secondary Education, Special Education, Physical Education, Music/Art Education)

Another Major (textbox)

Q43: Does your **terminal degree belong to the STEM field** (i.e., science, technology, engineering and mathematics)?

Yes

No

Not sure

Thank you for your time!

If you would like to receive aggregated study results, feel free to contact me by e-mail:

titaretn@jmu.edu

Appendix F

Themes and codes identified via responses to the survey open-ended question "What else do you think we should know that we haven't asked you about in relation to the intention to use AI-based EAS at JMU?"

Theme	Code	Respondent Statements
CONCERNS	**Overreliance on technology**	*"I worry that we will rely on technology to solve problems or force solutions to problems that don't really exist, rather than knowing what research questions we need to address that we can apply the technological tools to help explore."*
	Equity, inclusion, data privacy, transparency, and ethics	*"Equity, inclusion, data privacy, and ethics are important to consider and explain before an EAS adoption decision. It is also important to conduct a review of the literature and to gather case studies relating to adaptive technologies that have succeeded and failed to the detriment of student mental health and well-being. It would also help to present an explanation of the problem to be solved, and the benefit when pitching the idea. Labeling learners may lead to lower classroom performance, feelings of being singled-out, and perceived or real negative influence on grading and*

Theme	Code	Respondent Statements
		supports provided in the classroom. As a child my family was poor, from a poor town, and in college I discovered I had been predicted to graduate with a low GPA. I was shocked. The prediction was completely inaccurate, appeared biased due to my SES, and decades later I still remember this. Do not do this to our students at JMU without first addressing real or perceived issues and concerns relating to equity, inclusion, data privacy, and ethics. In another case, here at JMU, I can recall a student failing out-right. I finally had a good conversation with him and he was mad at his Dad for making him major in something he did not like in order to support him in college. He was a brick layer and could not sometimes get to school easily without a car. He had no advocate. On the other hand, he was competent and able to succeed in the course. On what basis, and for what purpose, will the EAS be used? How will it make a decision/prediction? What data will feed into it? These are questions that would be helpful to have an answer to."

Theme	Code	Respondent Statements
	Plagiarism issues	*"I am concerned about students' using AI for paper writing and assignments. As the technology improves, I am not sure we will be able to tell if the student actually wrote the paper or if they allowed the AI to do it for them. Will they learn how to write"*
	Bias	*"The issue of early alert systems can reflect, even unintentional bias. It is also hard to build in the complexities of living as a diverse person because much of that experience is the intersection of the individual experience with the environment and histories of all. Political impact, as witnessed by the role back of more progressive inclusionary policies and practices to the structural barriers of settler colonialism, genocides, and other harm that are still felt/experienced by descendants."*

Theme	Code	Respondent Statements
	Lack of AI tools' regulations	*"Predictive analysis, while it has bonafide applications, is - in my opinion - an inherently risky, if not openly dangerous technology to use in regard to predicting the actions of individuals. It cannot factor in elements such as emotional strengths or failings, random events that detract from studies or other areas of life, as well as numerous other areas of life. Additionally, while I understand this is a hypothetical question, there are no laws regulating AI, and there are few laws governing predictive analysis. While not inherently wrong or detrimental, I do believe that such technologies absolutely require more rigorous study, development, and open discussion prior to even considering using AI to predict the success or failure of a human being, either in academics or any other area of life."*
	Proficiency in AI: faculty vs. students	*"I am concerned that professors will struggle to use AI effectively and students will use AI to do their homework for them."*

Theme	Code	Respondent Statements
	Legal liability	*"Using AI technologies does not eliminate the extra workload an EAS creates for current employees, nor the legal liability that could come from predictions about a student's future struggles."*
REQUIRED ACTIONS /CHANGES	**Culture change**	*"Have previously used an EAS at a prior institution. I am familiar with EAS systems and saw immediate positive impacts on students and case management. That being said, successful implementation is a culture change - technology is not a solution. If an EAS is not adopted widely, I can see myself not seeing the system as worth my time."*
	Responsible in HE for reviewing AI policies	*"Who is reviewing the policies of usage and what would be the impact of such use in the lives of students."*
	To see/explain/communicate the "value add" of the tools	*"Adoption and usage is fundamentally related to seeing/understanding that there is value-added to the mission of the institution and the day-to-day*

Theme	Code	Respondent Statements
		experience of users. Changes in technology have impacted generations of higher education professionals and students for decades. All changes require a significant investment in time and without a clear vision of 'value added' it's all to easy (understandably) to make a short-term decision not to invest. Oftentimes the focus is on the 'tool' rather than a focus on 'how to best use a tool to solve a problem/meet a need.' Tools that are practical, address multiple needs in, and can be used proficiently are worth the investment."
	Training for proper integration of AI tools	*"I consider AI-based EAS a tool that enhances our ability to do our job; it doesn't replace critical thinking or integrating that information into more complex decision-making or conversations with the student; I am most concerned about adequate and scaled training to help integrate usage of the tool appropriately.*"
	Protocols and procedures in place	*"What will the protocols and procedures be in terms of the oversight and approval of various AI based initiatives at JMU?"*

Theme	Code	Respondent Statements
	Teaching students responsible use of AI tools	*"This survey did not address the use of AI tools in modern data analysis, nor effective approaches to teaching students responsible use of AI tools. Also, the survey did not address equity issues with the use of AI tools. Seems to me that these are important topics to include in data collection efforts with regard to this thesis."*
	Need to learn more about both the technology and ethical implications before it is used on mass scale	*"This survey is the first time I have had the opportunity to think about this. It is all new to me. I do not feel I know enough to make good judgements. However, it seems important that I learn more about both the technology and ethical implications before this all becomes a reality."*
	Proper preparation before adoption	*"I think we should be thoughtful and prepared."*
OTHER	**AI tools' use in different areas of HE** (SA Residence life, etc.)	*"I work in residence life, I'm wondering how an AI software could be used to assign students into housing and create the best living environment for them. Or even to help RAs model programs based around their students likes and dislikes."*

Theme	Code	Respondent Statements
	Differences for instructional vs. non-instructional staff	*"I work in a non-instructional academic unit so many of the questions did not apply directly to my work. however, I commented on our leadership's view of technology and certain aspects thereof."*
	AI use for safety	*"AI could be used for safety."*

References

Afshari, M., Bakar K.A., Luan W.S., Samah B.A., & Fooi, F.S. (2009). Technology and School Leadership, Technology. *Pedagogy and Education*, *18*(2), 235-248. https://doi.org/10.1080/14759390902992527

Aguilar, S., Lonn, S., & Teasley, S. D. (2014, March). Perceptions and use of an early warning system during a higher education transition program. In *Proceedings of the fourth international conference on learning analytics and knowledge*, 113-117. https://doi.org/10.1145/2567574.2567625

Ajzen, I. (1991). The Theory of Planned Behavior. *Organizational Behavior and Human Decision Processes*, *50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I., & Fishbein, M. (1974). Factors influencing intentions and the intention-behavior relation. *Human Relations*, *27*(1), 1–15. https://doi.org/10.1177/001872677402700101

Akçapınar, G., Altun, A., & Aşkar, P. (2019). Using learning analytics to develop early-warning system for at-risk students. *International Journal of Educational Technology in Higher Education*, *16*(1), 1-20. https://doi.org/10.1186/s41239-019-0172-z

Al-Ghnimi, S., Al-Maskari, A., & Al-Riyami, T. (2022). A Framework to Measure Higher Education Institutions' Readiness for the Fourth Industrial Revolution. *NeuroQuantology*, *20*(10), 7436-7445. 10.14704/nq.2022.20.10.NQ55733

Anderson, R. E., & Dexter, S. L. (2000). School Technology Leadership: Incidence and Impact. *Teaching, Learning, and Computing*: 1998 National Survey, Report# 6.

Anderson, R.E., & Dexter, S. (2005). School Technology Leadership: An Empirical

Investigation of Prevalence and Effect. *Educational Administration Quarterly*, *41*(1), 49–82. https://doi.org/10.1177/ 0013161X04269517

Aoun, J. E. (2017). *Robot-Proof: Higher Education in the Age of Artificial Intelligence*. MIT press. https://doi.org/10.7551/mitpress/11456.001.0001

Araka, E., Maina, E., Gitonga, R., & Oboko, R. (2020). Research trends in measurement and intervention tools for self-regulated learning for e-learning environments—systematic review (2008–2018). *Research and Practice in Technology Enhanced Learning*, *15*, 1-21. https://doi.org/10.1186/s41039-020-00129-5

Arnold, K. E., Lonn, S., & Pistilli, M. D. (2014). An exercise in institutional reflection: The learning analytics readiness instrument (LARI). *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge*, 163–167. https://doi.org/10.1145/2567574.2567621

Arnold, K. E., & Pistilli, M. D. (2012). Course signals at Purdue: using learning analytics to increase student success. *Proceedings of the 2nd International Conference on Learning Analytics and Knowledge*, 267–270. https://doi.org/10.1145/2330601.2330666

Arroway, P., Morgan, G., O'Keefe, M. & Yanosky, R. (2016) *Learning Analytics in Higher Education*. Research report. Louisville, CO: ECAR. EDUCAUSE 2016. https://library.educause.edu/~/media/files/library/2016/2/ers1504la

Asabin, V. V., Garanin, M. A., Gnatyuk, M. A., Klimova, A. S., & Pervov, P. A. (2019). "Blue Ocean" For A Higher School. *Dilemas Contemporáneos: Educación, Política y Valore*, *6*(Special).

Austin, A. E., & Sorcinelli, M. D. (2013). The future of faculty development: Where are we going? *New Directions for Teaching and Learning*, *2013*(133), 85–97. https://doi.org/10.1002/tl.20048

Avolio, B. J., Kahai, S., & Dodge, G. E. (2000). E-leadership: Implications for theory, research, and practice. *The Leadership Quarterly*, *11*(4), 615-668. https://doi.org/10.1016/S1048-9843(00)00062-X

Avolio, B. J., Sosik, J. J., Kahai, S. S., & Baker, B. (2014). E-leadership: Re-examining transformations in leadership source and transmission. *The Leadership Quarterly*, *25*(1), 105-131. https://doi.org/10.1016/j.leaqua.2013.11.003

Aybek, H. S. Y., & Okur, M. R. (2018). Predicting achievement with artificial neural networks: the case of Anadolu university open education system. *International Journal of Assessment Tools in Education*, *5*(3), 474-490. DOI: 10.21449/ijate.435507

Bagranoff, N., & Bryant, S. (2020). Business education and technology: an AACSB perspective. In *Handbook of Teaching with Technology in Management, Leadership, and Business*, 96-101. Edward Elgar Publishing. https://doi.org/10.4337/9781789901658.00018

Ball, D.M. (2016). *Using Early Alert Data to Increase Success Rates Among U.S. Community College Students*. ProQuest Dissertations Publishing.

Baltaci-Goktalay, S., & Ocak, M. A. (2006). Faculty Adoption of Online Technology in Higher Education. *TOJET the Turkish Online Journal of Educational Technology*, *5*(4).

Bañeres, D., Rodríguez, M. E., Guerrero-Roldán, A. E., & Karadeniz, A. (2020). An Early Warning System to Detect At-Risk Students in Online Higher Education. *Applied Sciences*, *10*(13), 4427–. https://doi.org/10.3390/app10134427

Bañeres, D., Rodríguez-González, M. E., Guerrero-Roldán, A. E., & Cortadas, P. (2023). An early warning system to identify and intervene online dropout learners. *International Journal of Educational Technology in Higher Education*, *20*(1), 1-25. https://doi.org/10.1186/s41239-022-00371-5

Barefoot, B.O. (2004). Higher education's revolving door: confronting the problem of student drop out in US colleges and universities. *Open Learning*, *19*(1), 9–18. https://doi.org/10.1080/0268051042000177818

Barnato, K. (2016, January 23). Is the world suffering from a leadership crisis? *CNBC*. https://www.cnbc.com/2016/01/23/is-the-world-suffering-from-a-leadership-crisis.html

Barrett, M., Branson, L., Carter, S., DeLeon, F., Ellis, J., Gundlach, C., & Lee, D. (2019). Using Artificial Intelligence to Enhance Educational Opportunities and Student Services in Higher Education. *Inquiry: The Journal of the Virginia Community Colleges*, *22* (1). https://commons.vccs.edu/inquiry/vol22/iss1/11

Bartlett, T. (2020, August 7). Mitch Daniels Has Not Changed His Mind. *The Chronicle of Higher Education*. https://www.chronicle.com/article/mitch-daniels-has-not-changed-his-mind

Bates, C., Cobo, C., Mariño, O., & Wheeler, S. (2020). Can artificial intelligence transform higher education? *International Journal of Educational Technology in Higher Education*, *17*(1), 1–12. https://doi.org/10.1186/s41239-020-00218-x

Becker, B. (2017). Artificial intelligence in education: what is it, where is it now, where is it going. *Ireland's Yearbook of Education*, *2018*, 42-46. https://www.brettbecker.com/wp-content/uploads/2019/04/Becker-AI-in-Education-with-cover-sheet.pdf

Bentham, C. (2017). Faculty perspectives and participation in implementing an early alert system and intervention in a community college. *STARS Electronic Theses and Dissertations. University of Central Florida.*

Bento, F. (2011). A discussion about power relations and the concept of distributed leadership in higher education institutions. *The Open Education Journal*, *4*(1). https://doi.org/10.2174/1874920801104010017

Bichsel, J. (2012). *Analytics in Higher Education: Benefits, Barriers, Progress, and Recommendations*. EDUCAUSE Center for Applied Research.

Blut, M., Chong, A., Tsiga, Z., & Venkatesh, V. (2022). Meta-Analysis of the Unified Theory of Acceptance and Use of Technology (UTAUT): Challenging its Validity and Charting a Research Agenda in the Red Ocean. *Journal of the Association for Information Systems*, *23*(1), 13–95. https://doi.org/10.17705/1jais.00719

Brock, J. K. U., & Von Wangenheim, F. (2019). Demystifying AI: What digital transformation leaders can teach you about realistic artificial intelligence. *California Management Review*, *61*(4), 110-134. https://doi.org/10.1177/1536504219865226

Brosnan, M. J. (1999). Modeling technophobia: A case for word processing. *Computers in Human Behavior*, *15*(2), 105-121. https://doi.org/10.1016/s0747-5632(98)00020-x

Brosnan, M. J. (1998). Technophobia: The psychological impact of information technology. London: Routledge.

Campbell, J. P., DeBlois, P. B., & Oblinger, D. G. (2007). Academic Analytics: A New Tool for a New Era. *EDUCAUSE Review*, *42*(4), 40–.

Campbell, J. P., Finnegan, C., & Collins, B. (2006, July). Academic analytics: Using the CMS as an early warning system. In *WebCT Impact Conference*.

Cele, N. (2021). Big data-driven early alert systems as means of enhancing university student retention and success. *South African Journal of Higher Education*, *35*(2), 56-72. https://doi.org/10.20853/35-2-3899

Charles and Lynn Schusterman Family Foundation (2020). *More than numbers: Guide Toward Diversity, Equity, and Inclusion (DEI) in Data Collection*. https://www.schusterman.org/more-than-numbers-a-guide-toward-diversity-equity-and-inclusion-dei-in-data-collection

Chatterjee, B., & Bhattacharjee, K. K. (2020). Adoption of artificial intelligence in higher education: a quantitative analysis using structural equation modelling. *Education and Information Technologies*, *25*(5), 3443–3463. https://doi.org/10.1007/s10639-020-10159-7

Chen, H. (2019). *Success Factors Impacting Artificial Intelligence Adoption: Perspective from the Telecom Industry in China*. ProQuest Dissertations Publishing.

Chowdhury, S., Dey, P., Joel-Edgar, S., Bhattacharya, S., Rodriguez-Espindola, O., Abadie, A., & Truong, L. (2023). Unlocking the value of artificial intelligence in human resource management through AI capability framework. *Human Resource Management Review*, *33*(1), 100899. https://doi.org/10.1016/j.hrmr.2022.100899

Chronicle of Higher Education (2023, May 25). *How Will Artificial Intelligence Change Higher Ed? ChatGPT is just the beginning. 12 scholars and administrators begin*. https://www.chronicle.com/article/how-will-artificial-intelligence-change-higher-ed

Chua, Y. P., & Chua, Y. P. (2017). How are e-leadership practices in implementing a school virtual learning environment enhanced? A grounded model study. *Computers & Education*, *109*, 109-121. https://doi.org/10.1016/j.compedu.2017.02.012

Chung, J. Y., & Lee, S. (2019). Dropout early warning systems for high school students using machine learning. *Children and Youth Services Review*, *96*, 346–353. https://doi.org/10.1016/j.childyouth.2018.11.030

Ciolacu, M., Tehrani, A. F., Binder, L., & Svasta, P. M. (2018). Education 4.0-Artificial Intelligence Assisted Higher Education: Early recognition System with Machine Learning to support Students' Success. In *2018 IEEE 24th International Symposium for Design and Technology in Electronic Packaging (SIITME)*. 23-30. IEEE. https://doi.org/10.1109/siitme.2018.8599203

Cohen, J., Cohen, P., West, S. G., & Aiken, L. S. (2013). *Applied multiple regression/correlation analysis for the behavioral sciences*. Routledge. https://doi.org/10.4324/9780203774441

Colvin, C., Dawson, S., Wade, A., & Gašević, D. (2017). Addressing the challenges of institutional adoption. *Handbook of Learning Analytics*, *1*, 281-289. https://doi.org/10.18608/hla17.024

Colvin, C., Rogers, T., Wade, A., Dawson, S., Gašević, D., Shum, S.B., & Fisher, J. (2015). *Student retention and learning analytics: A snapshot of Australian practices and a framework for advancement*. Sydney: Australian Office for Learning and Teaching.

Creswell, J.W., & Creswell, J.D. (2018). *Research Design: Qualitative, Quantitative, and Mixed Methods Approaches. 5th edition*. Los Angeles: Sage.

Cribben, I., & Zeinali, Y. (2023). The Benefits and Limitations of ChatGPT in Business Education and Research: A Focus on Management Science, Operations Management and Data Analytics. *Operations Management and Data Analytics*. https://doi.org/10.2139/ssrn.4404276

Dahlstrom, E., Brooks, D. C., & Bichsel, J. (2014, September). *The Current Ecosystem of*

Learning Management Systems in Higher Education: Student, faculty, and IT perspectives (Research report). Louisville, CO: EDUCAUSE.

DasGupta, P. (2011). Literature review: e-Leadership. *Emerging Leadership Journeys*, *4*(1), 1-36.

Davidson, B. I., Ellis, D., Bowman, N., Liveley, G., Shaw, H., Przybylski, A. K., & Levine, M. (2019). *Avoiding irrelevance: The manifestation and impacts of technophobia in psychological science*. https://doi.org/10.31234/osf.io/b9f4p

Davis, F. D. (1989). Technology acceptance model: TAM. *Al-Suqri, MN, Al-Aufi, AS: Information Seeking Behavior and Technology Adoption*, 205-219.

Dawson, S., Jovanovic, J., Gašević, D., & Pardo, A. (2017, March). From prediction to impact: Evaluation of a learning analytics retention program. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference.* 474-478. https://doi.org/10.1145/3027385.3027405

Deakin University (2015, November 25). *IBM Watson now powering Deakin. A new partnership that aims to exceed students' needs*. https://www.deakin.edu.au/about-deakin/news-and-media-releases/articles/ibm-watson-helps-deakin-drive-the-digital-frontier

Demirci, A. E., & Ersoy, N. F. (2008). Technology readiness for innovative high-tech products: how consumers perceive and adopt new technologies. *The Business Review*, *11*(1), 302-308.

Dexter, S., & Barton, E. A. (2021). The development and impact of team-based school technology leadership. *Journal of Educational Administration*, *59*(3), 367–384. https://doi.org/10.1108/jea-12-2020-0260

Diamandis, P. H., & Kotler, S. (2020). *The Future is Faster Than You Think: How Converging*

Technologies Are Transforming Business, Industries, and Our Lives. Simon & Schuster.

Dishaw, M. T., & Strong, D. M. (1999). Extending the technology acceptance model with task–technology fit constructs. *Information & Management, 36*(1), 9–21. https://doi.org/10.1016/S0378-7206(98)00101-3

Dittmar, J. E. (2011). Information technology and economic change: the impact of the printing press. *The Quarterly Journal of Economics*, *126*(3), 1133–1172. https://doi.org/10.1093/qje/qjr035

Dumas, C., & Beinecke, R. H. (2018). Change leadership in the 21st century. *Journal of Organizational Change Management*, *31*(4), 867-876. https://doi.org/10.1108/JOCM-02-2017-0042

Dwyer, L.R. (2017). *An Analysis of the Impact of Early Alert on Community College Student Persistence in Virginia*. ProQuest Dissertations Publishing.

Ehlers, U. D. (2020). Digital leadership in higher education. *Journal of Higher Education Policy and Leadership Studies, 1*(3), 6-14. https://dx.doi.org/10.29252/johepal.1.3.6

Elbadrawy, A., Polyzou, A., Ren, Z., Sweeney, M., Karypis, G., & Rangwala, H. (2016). Predicting Student Performance Using Personalized Analytics. *Computer (Long Beach, Calif.)*, *49*(4), 61–69. https://doi.org/10.1109/MC.2016.119

Elbadrawy, A., Studham, R. S., & Karypis, G. (2015). Collaborative multi-regression models for predicting students' performance in course activities. In *Proceedings of the Fifth International Conference on Learning Analytics and Knowledge* (LAK). 103–107. New York, NY: Association for Computing Machinery. https://doi.org/10.1145/2723576.2723590

Elhai, J. D., Dvorak, R. D., Levine, J. C., & Hall, B. J. (2017). Problematic smartphone use: A conceptual overview and systematic review of relations with anxiety and depression psychopathology. *Journal of Affective Disorders*, *207*, 251–259. https://doi.org/10.1016/j.jad.2016.08.030

FakhrHosseini, S., Chan, K., Lee, C., Jeon, M., Son, H., Rudnik, J., & Coughlin, J. (2022). User Adoption of Intelligent Environments: A Review of Technology Adoption Models, Challenges, and Prospects. *International Journal of Human–Computer Interaction*, 1-13. https://doi.org/10.1080/10447318.2022.2118851

Ferguson, R., Clow, D., Macfadyen, L., Essa, A., Dawson, S., & Alexander, S. (2014). Setting learning analytics in context: overcoming the barriers to large-scale adoption. *Proceedings of the Fourth International Conference on Learning Analytics and Knowledge*, 251–253. ACM. https://doi.org/10.18608/jla.2014.13.7

Fishbein, M., & Ajzen, I. (1975). Belief, Attitude, Intention, and Behavior. Reading, MA: Addison-Wesley.

Flanagan, L., & Jacobsen, M. (2003). Technology leadership for the twenty-first century principal. *Journal of Educational Administration*. *41*(2), 124-142. https://doi.org/10.1108/09578230310464648

Fram, E. H., & Grady, D. B. (1997). Internet shoppers: Is there a surfer gender gap? *Direct Marketing-Garden City*. *59*, 46-51.

Friesen, N. (2013). Learning Analytics: Readiness and Rewards / L'analyse de l'apprentissage: état de préparation et récompenses. *Canadian Journal of Learning and Technology*, *39*(4), 1–. https://doi.org/10.21432/T2J01B

Fritz, J. (2013). Using analytics at UMBC: Encouraging student responsibility and identifying effective course designs. *EDUCAUSE Center for Applied Research*, 1-11.

Gates, W.H. (2023, March 21). The Age of AI has begun. Artificial intelligence is as revolutionary as mobile phones and the Internet. *GatesNotes The Blog of Bill Gates*. https://www.gatesnotes.com/The-Age-of-AI-Has-Begun

Gilbert, D., Kelley, L., & Barton, M. (2003). Technophobia, gender influences and consumer decision-making for technology-related products. *European Journal of Innovation Management*, *6*(4), 253–263. https://doi.org/10.1108/14601060310500968

Gilroy, F. D., & Desai, H. B. (1986). Computer anxiety: sex, race and age. *International Journal of Man-Machine Studies*, *25*(6), 711–719. https://doi.org/10.1016/S0020-7373(86)80084-0

Godoe, P., & Johansen, T. (2012). Understanding adoption of new technologies: Technology readiness and technology acceptance as an integrated concept. *Journal of European Psychology Students*, *3*(1), 38–52. https://doi.org/10.5334/jeps.aq

Goldman Sachs (2023, March). Global Economics Analyst. The Potentially Large Effects of Artificial Intelligence on Economic Growth (Briggs/Kodnani). *Goldman Sachs Economics Research*. https://www.key4biz.it/wp-content/uploads/2023/03/Global-Economics-Analyst_-The-Potentially-Large-Effects-of-Artificial-Intelligence-on-Economic-Growth-Briggs_Kodnani.pdf

Goldstein, P. J., & Katz, R. N. (2005). *Academic Analytics: The Uses of Management Information and Technology in Higher Education. 8*(1), 1-12. Educause.

Goldsworthy, A. (2011). How Smart Meters May Cause Autism and Cancer. *Scientific Paradigm Review*.

Google DeepMind (2020). AlphaGo - The Movie | Full award-winning documentary. *Youtube*. https://www.youtube.com/watch?v=WXuK6gekU1Y&t=16s

Gurr, D. (2004). ICT, Leadership in Education and E-leadership. *Discourse (Abingdon, England)*, *25*(1), 113–124. https://doi.org/10.1080/0159630042000178518

Gutek, B. A., & Bikson, T. K. (1985). Differential experiences of men and women in computerized offices. *Sex Roles*, *13*(3-4), 123–136. https://doi.org/10.1007/BF00287905

Haenlein, M., & Kaplan, A. (2019). A brief history of artificial intelligence: On the past, present, and future of artificial intelligence. *California Management Review*, *61*(4), 5-14. https://doi.org/10.1177/0008125619864925

Harrison, A. W., & Rainer Jr, R. K. (1992). The Influence of Individual Differences on Skill in End-User Computing. *Journal of Management Information Systems*, *9*(1), 93–111. https://doi.org/10.1080/07421222.1992.11517949

Harvard University Center for Education Policy Research (2020, June). Strategic Data Use in Higher Education. Improving Postsecondary Success with Data. *Center For Education Policy Research at Harvard University.* https://cepr.harvard.edu/files/cepr/files/wp_sdp_he_final_1_01.pdf

Hertzog, C., & Hultsch, D. F. (2000). Metacognition in adulthood and old age. In F. I. M. Craik & T. A. Salthouse (Eds.), *The Handbook of Aging and Cognition.* 417–466. Lawrence Erlbaum Associates Publishers.

Hickman, L., & Akdere, M. (2017). Integrated Literature Review of Information Technology Leadership in Higher Education: Implications for Total Quality Management. *4th International Conference on Lean Six Sigma for Higher Education*. https://doi.org/10.5703/1288284316380

Hilgard, E. R., & Bower, G. H. (1975). *Theories of Learning*. New Jersey, Prentice-Hall. Inc.

Hinojo-Lucena, F. J., Aznar-Díaz, I., Cáceres-Reche, M. P., & Romero-Rodríguez, J. M. (2019).

Artificial Intelligence in Higher Education: A Bibliometric Study on its Impact in the Scientific Literature. *Education Sciences*, *9*(1), 51–. https://doi.org/10.3390/educsci9010051

Hogan, M. (2008). Age differences in technophobia: an Irish study. In *Information Systems Development: Challenges in Practice, Theory, and Education. 1*, 117-130. Boston, MA: Springer US. https://doi.org/10.1007/978-0-387-68772-8_10

Hollingsworth, M., Mrazek, R., Steed, M., Spence, G., Percevault, J., Balding, P., & Burnett, D. (2004). Information technology leadership in education: An Alberta needs assessment. *Learning and Technology Research, Stakeholder Technology Branch.* Alberta Learning. Edmonton, Alberta.

Hughes, A. (2010). *Digital Media Development in Education University of Limerick* (Doctoral dissertation, Master thesis, University of Limerick).

Hurt, A. C., & Deadman, R. C., & Daugherty, J., & Lybrook, D. O. (2014). Pathways to Technology Leadership. Paper presented at *2014 ASEE Annual Conference & Exposition*, Indianapolis, Indiana. https://doi.org/10.18260/1-2--22906

Hwang, G. J., Xie, H., Wah, B. W., & Gašević, D. (2020). Vision, challenges, roles and research issues of Artificial Intelligence in Education. *Computers and Education. Artificial Intelligence*, *1*, 100001–. https://doi.org/10.1016/j.caeai.2020.100001

Igbaria, M., & Parasuraman, S. (1989). A path analytic study of individual characteristics, computer anxiety and attitudes toward microcomputers. *Journal of Management*, *15*(3), 373-388. https://doi.org/10.1177/014920638901500302

Issroff, K., & Scanlon, E. (2002). Educational Technology: The Influence of Theory. *Journal of Interactive Media in Education: JiME*, *2002*(1), 6–. https://doi.org/10.5334/2002-6

Johnson, L., Adams, S., and Cummins, M. (2012). *The NMC Horizon Report: 2012 Higher Education Edition*. Austin, Texas: The New Media Consortium. https://eric.ed.gov/?id=ED532397

Johnson, L., Smith, R., Willis, H., Levine, A., & Haywood, K. (2006). *The 2011 Horizon Report*. Austin, Texas: The New Media Consortium. https://eric.ed.gov/?id=ED515956

Jones, V. K. (2018). Voice-activated change: Marketing in the age of artificial intelligence and virtual assistants. *Journal of Brand Strategy*, *7*(3), 233-245.

Joo, Y. J., Lim, K. Y., & Kim, N. H. (2016). The effects of secondary teachers' technostress on the intention to use technology in South Korea. *Computers & Education*, *95*, 114-122. https://doi.org/10.1016/j.compedu.2015.12.004

Karakose, T., Kocabas, I., Yirci, R., Papadakis, S., Ozdemir, T. Y., & Demirkol, M. (2022). The Development and Evolution of Digital Leadership: A Bibliometric Mapping Approach-Based Study. *Sustainability (Basel, Switzerland)*, *14*(23), 16171–. https://doi.org/10.3390/su142316171

Kearsley, G. (1994). *Educational technology: Leadership perspectives*. Educational Technology.

Keengwe, J., Kidd, T., & Kyei-Blankson, L. (2009). Faculty and Technology: Implications for Faculty Training and Technology Leadership. *Journal of Science Education and Technology*, *18*(1), 23–28. https://doi.org/10.1007/s10956-008-9126-2

Kelchen, R. (2018). *Higher Education Accountability*. Johns Hopkins University Press. https://doi.org/10.1353/book.58123

Khasawneh, O. (2018). Technophobia without boarders: The influence of technophobia and emotional intelligence on technology acceptance and the moderating influence of organizational climate. *Computers in Human Behavior*, *88*, 210–218. https://doi.org/10.1016/j.chb.2018.07.007

Khasawneh, O. (2015). *The Impact of Technophobia on Technology Acceptance and the Moderating Influence of Transformational Leadership, Organizational Climate, and Emotional Intelligence*. ProQuest Dissertations Publishing.

Khasawneh, O. & Bellamy, A. (2014). *Technophobia scale*. Unpublished work.

Kelly (2023, March 31). Goldman Sachs Predicts 300 Million Jobs Will Be Lost Or Degraded By Artificial Intelligence. *Forbes*. https://www.forbes.com/sites/jackkelly/2023/03/31/goldman-sachs-predicts-300-million-jobs-will-be-lost-or-degraded-by-artificial-intelligence/?sh=d318ad2782b4

Kezar, A. (2018). *How colleges change: Understanding, leading, and enacting change*. Routledge. https://doi.org/10.4324/9781315121178

King, W. R., & He, J. (2006). A meta-analysis of the technology acceptance model. *Information & Management*, *43*(6), 740–755. https://doi.org/10.1016/j.im.2006.05.003

Klein, C., Lester, J., Rangwala, H., & Johri, A. (2019). Learning analytics tools in higher education: Adoption at the intersection of institutional commitment and individual action. *The Review of Higher Education*, *42*(2), 565-593. https://doi.org/10.1353/rhe.2019.0007

Korukonda, A. R. (2005). Personality, Individual Characteristics, and Predisposition to Technophobia: Some Answers, Questions, and Points to Ponder about, *Information Sciences*, *170*, 309–328. https://doi.org/10.1016/j.ins.2004.03.007

Kotze, T. G., Anderson, O., & Summerfield, K. (2016). Technophobia: gender differences in the adoption of high-technology consumer products. *South African Journal of Business Management*, *47*(1), 21–28. https://doi.org/10.4102/sajbm.v47i1.49

Koul, S. (2017). *An Investigation of Factors Impacting Driverless Car Technology Adoption Within the United States*. ProQuest Dissertations Publishing.

Krishna, K. V., Kumar, M., & Sri, P. S. G. (2018). Student information system and performance retrieval through dashboard. *International Journal of Engineering and Technology (UAE)*, *7*, 682-685.

Lai, P. C. (2017). The literature review of technology adoption models and theories for the novelty technology. *Journal of Information Systems and Technology Management*, *14*(1), 21–38. https://doi.org/10.4301/S1807-17752017000100002

Lapteva, A. V., & Efimov, V. S. (2016). *New generation of universities. University 4.0*. Journal of Siberian Federal University. *Humanities & Social Sciences, 11* (2016 9), 2681-2696. https://doi.org/10.17516/1997-1370-2016-9-11-2681-2696

Legris, P., Ingham, J., & Collerette, P. (2003). Why do people use information technology? A critical review of the technology acceptance model. *Information & Management, 40*(3), 191–204. https://doi.org/10.1016/s0378-7206(01)00143-4

Lester, J., Klein, C., Rangwala, H., & Johri, A. (2017). Learning Analytics in Higher Education. *ASHE Higher Education Report*, *43*(5), 9–135. https://doi.org/10.1002/aehe.20121

Li, S., Glass, R., & Records, H. (2008). The Influence of Gender on New Technology Adoption and Use-Mobile Commerce. *Journal of Internet Commerce*, *7*(2), 270–289. https://doi.org/10.1080/15332860802067748

Liu, C., Ready, D., Roman, A., Van Wart, M., Wang, X., McCarthy, A., & Kim, S. (2018). E-leadership: an empirical study of organizational leaders' virtual communication adoption. *Leadership & Organization Development Journal*, *39*(7), 826-843. https://doi.org/10.1108/lodj-10-2017-0297

Lotfizadeh, F., & Ghorbani, A. (2015). A multi-dimensional model of acceptance of mobile banking. *International Journal of Management, Accounting and Economics*, *2*(5), 414-427.

Luckin, R., Holmes, W., Griffiths, M., & Forcier, L. B. (2016). Intelligence unleashed: An argument for AI in education. *UCL Discovery*. https://discovery.ucl.ac.uk/id/eprint/1475756/

Lukovics, M., & Zuti, B. (2017, September 4). Successful Universities towards the Improvement of Regional Competitiveness: 'Fourth Generation' Universities. *SSRN*. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3022717

Lupack, B. T. (1983). *Early Alert: Reaching Students in Time*. https://eric.ed.gov/?id=ED239568

Lynch, S. (2017, March 11). Andrew Ng: Why AI Is the New Electricity. *Stanford Graduate School of Business Insights*. https://www.gsb.stanford.edu/insights/andrew-ng-why-ai-new-electricity

Macfadyen, L. P., & Dawson, S. (2012). Numbers are not enough. Why e-learning analytics failed to inform an institutional strategic plan. *Journal of Educational Technology & Society*, *15*(3), 149-163.

Madden, T. J., Ellen, P. S., & Ajzen, I. (1992). A comparison of the theory of planned behavior and the theory of reasoned action. *Personality and Social Psychology Bulletin*, *18*(1), 3–9. https://doi.org/10.1177/0146167292181001

Malhotra, Y., & Galletta, D. F. (1999). Extending the technology acceptance model to account for social influence: Theoretical bases and empirical validation. *Proceedings of the 32nd Hawaii International Conference on System Sciences*, Maui, Hawaii, USA, 1-14. doi:10.1109/HICSS.1999.772658

Marescotti, M. E., Demartini, E., Filippini, R., & Gaviglio, A. (2021). Smart farming in mountain areas: Investigating livestock farmers' technophobia and technophilia and their perception of innovation. *Journal of Rural Studies*, *86*, 463-472. https://doi.org/10.1016/j.jrurstud.2021.07.015

Marr, B. (2019, December 16). The 10 Best Examples Of How AI Is Already Used In Our Everyday Life. *Forbes*. https://www.forbes.com/sites/bernardmarr/2019/12/16/the-10-best-examples-of-how-ai-is-already-used-in-our-everyday-life/#51404a271171

Masrur, M. (2021). Digital Leadership to Improve the Pedagogical Competence of University English Lecturers in Samarinda. *Journal of Social Studies Education Research*, *12*(4), 424–446.

McCartney, A. (2023, April 5). Your 7 Biggest ChatGPT Questions, Answered. *Gartner*. https://www.gartner.com/en/articles/your-7-biggest-chatgpt-questions-answered

McGee, J. (2015). Breakpoint: The Changing Marketplace for Higher Education. JHU Press.

McKinsey & Company (2023, January 19). *What is generative AI?* https://www.mckinsey.com/featured-insights/mckinsey-explainers/what-is-generative-ai

McKinsey & Company (2023, June 14). *The economic potential of generative AI: The next productivity frontier*. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-economic-potential-of-generative-ai-the-next-productivity-frontier#/

McLean, S., Read, G. J., Thompson, J., Baber, C., Stanton, N. A., & Salmon, P. M. (2023). The risks associated with Artificial General Intelligence: A systematic review. *Journal of Experimental & Theoretical Artificial Intelligence*, *35*(5), 649-663. https://doi.org/10.1080/0952813x.2021.1964003

Miller, C. E. (2019). Leading Digital Transformation in Higher Education: a Toolkit for Technology Leaders. In *Technology Leadership for Innovation in Higher Education,* 1-25. IGI Global. https://doi.org/10.4018/978-1-5225-7769-0.ch001

National Science Foundation National Center for Science and Engineering Statistics (2023, January 27). *National Survey of College Graduation: 2021, NSF 23-306*. https://ncses.nsf.gov/pubs/nsf23306

Nestik, T., Zhuravlev, A., Eduard, P., Marianna, S. C., Lioudmila, B., Piurcosky, F. P., & Ferreira, J. V. (2018). Technophobia as a cultural and psychological phenomenon: Theoretical analysis. *Interação-Revista De Ensino, Pesquisa E Extensão*, *20*(1), 266-281. https://doi.org/10.1108/14601060310500968

Nickell, G. S., & Pinto, J. N. (1986). The computer attitude scale. *Computers in Human Behavior*, *2*(4), 301–306. https://doi.org/10.1016/0747-5632(86)90010-5

Norris, D. M., & Baer, L. L. (2013). Building organizational capacity for analytics. *EDUCAUSE Learning Initiative*, 7–56. http://www.educause.edu/library/resources/building-organizationalcapacity-analytics

OECD (2023). *G7 Hiroshima Process on Generative Artificial Intelligence (AI): Towards a G7 Common Understanding on Generative AI*. OECD Publishing, Paris. https://doi.org/10.1787/bf3c0c60-en.

OECD (2019). *Artificial Intelligence in Society*. OECD Publishing, Paris. https://doi.org/10.1787/eedfee77-en.

OpenAI (2022). *Introducing ChatGPT*. https://openai.com/blog/chatgpt

Osiceanu, M. E. (2015). Psychological Implications of Modern Technologies: "Technofobia" versus "Technophilia." *Procedia, Social and Behavioral Sciences*, *180*, 1137–1144. https://doi.org/10.1016/j.sbspro.2015.02.229

Oster, M., Lonn, S., Pistilli, M. D., & Brown, M. G. (2016). The Learning Analytics Readiness Instrument. In *Proceedings of the Sixth International Conference on Learning Analytics & Knowledge*, 173-182. https://doi.org/10.1145/2883851.2883925

Page, L. C., & Gehlbach, H. (2017). How an artificially intelligent virtual assistant helps students navigate the road to college. *SSRN Electronic Journal*, *3*(4), 1-12. https://doi.org/10.1177/2332858417749220

Page, L. C., & Gehlbach, H. (2018). How Georgia State University Used an Algorithm to Help Students Navigate the Road to College. *Harvard Business Review*. https://hbr.org/2018/01/how-georgia-state-university-used-an-algorithm-to-help-students-navigate-the-road-to-college

Parker, S. (1995). *Science Discoveries: Alexander Graham Bell*. Philadelphia, USA: Chelsea House Publishers.

Parker, D., Manstead, A. S., Stradling, S. G., Reason, J. T., & Baxter, J. S. (1992). Intention to commit driving violations: An application of the theory of planned behavior. *Journal of Applied Psychology*, *77*(1), 94–101. https://doi.org/10.1037/0021-9010.77.1.94

Peek, S. T., Wouters, E. J., Van Hoof, J., Luijkx, K. G., Boeije, H. R., & Vrijhoef, H. J. (2014). Factors influencing acceptance of technology for aging in place: A systematic review. *International Journal of Medical Informatics*, *83*(4), 235–248. https://doi.org/10.1016/j.ijmedinf.2014.01.004

Pierce, R., & Ball, L. (2009). Perceptions That May Affect Teachers' Intention to Use Technology in Secondary Mathematics Classes. *Educational Studies in Mathematics*, *71*(3), 299–317. https://doi.org/10.1007/s10649-008-9177-6

Pistilli, M. D., & Heileman, G. L. (2017). Guiding Early and Often: Using Curricular and Learning Analytics to Shape Teaching, Learning, and Student Success in Gateway Courses: Guiding Early and Often. *New Directions for Higher Education*, *2017*(180), 21–30. https://doi.org/10.1002/he.20258

Popenici, S. A., & Kerr, S. (2017). Exploring the impact of artificial intelligence on teaching and learning in higher education. *Research and Practice in Technology Enhanced Learning*, *12*(1), 1-13. https://doi.org/10.1186/s41039-017-0062-8

Porter, C. E., & Donthu, N. (2006). Using the technology acceptance model to explain how attitudes determine Internet usage: The role of perceived access barriers and demographics. *Journal of Business Research*, *59*(9), 999–1007. https://doi.org/10.1016/j.jbusres.2006.06.003

Privitera, G. J. (2019). *Research Methods for the Behavioral Sciences. 3rd edition.* Los Angeles: Sage.

Qian, Y., & Huang, G. (Eds.). (2019). *Technology Leadership for Innovation in Higher Education*. IGI Global. https://doi.org/10.4018/978-1-5225-7769-0

Rainer Jr, R. K., Laosethakul, K., & Astone, M. K. (2003). Are Gender Perceptions of Computing Changing over Time? *The Journal of Computer Information Systems*, *43*(4), 108–114. https://doi.org/10.1080/08874417.2003.11647540

Ratajczak, S. (2022). Digital leadership at universities–a systematic literature review.

In Forum Scientiae Oeconomia, *10*(4), 133-150. https://doi.org/10.23762/FSO_VOL10_NO4_7

Richardson, M., Hussain, Z., & Griffiths, M. D. (2018). Problematic smartphone use, nature connectedness, and anxiety. *Journal of Behavioral Addictions*, *7*(1), 109–116. https://doi.org/10.1556/2006.7.2018.10

Rocha, Á., Gonçalves, M. J. A., da Silva, A. F., Teixeira, S., & Silva, R. (2021). Leadership challenges in the context of university 4.0. A thematic synthesis literature review. *Computational and Mathematical Organization Theory*, 1-33. https://doi.org/10.1007/s10588-021-09325-0

Rojas-Méndez, J. I., Parasuraman, A., & Papadopoulos, N. (2017). Demographics, attitudes, and technology readiness: A cross-cultural analysis and model validation. *Marketing Intelligence & Planning*, *35*(1), 18-39. https://doi.org/10.1108/mip-08-2015-0163

Rogers, E. M. (1995). *The diffusion of innovations (4th ed.).* New York: Free Press.

Rosen, L. D., Sears, D. C., & Weil, M. M. (1987). Computerphobia. *Behavior Research Methods, Instruments, & Computers*, *19*(2), 167-179. https://doi.org/10.3758/bf03203781

Rudmann, J. (1992). *An Evaluation of Several Early Alert Strategies for Helping First Semester Freshmen at the Community College and A Description of the Newly Developed Early Alert Retention System (EARS) Software*. https://eric.ed.gov/?id=ED349055

Şahin, F., & Şahin, Y. L. (2022). Drivers of technology adoption during the COVID-19 pandemic: The motivational role of psychological needs and emotions for pre-service teachers. *Social Psychology of Education*, *25*(2-3), 567–592. https://doi.org/10.1007/s11218-022-09702-w

Scheffel, M., Drachsler, H., Stoyanov, S., & Specht, M. (2014). Quality Indicators for Learning Analytics. *Educational Technology & Society, 17*(4), 117–132.

Scheffel, M., Tsai, Y. S., Gašević, D., & Drachsler, H. (2019). Policy Matters: Expert Recommendations for Learning Analytics Policy. In *Transforming Learning with Meaningful Technologies*, 510–524. Springer International Publishing. https://doi.org/10.1007/978-3-030-29736-7_38

Schwab, K. (2017). *The fourth industrial revolution*. Currency.

Selingo, J.J. (2023, May 25). AI Will Help Control Costs. *The Chronicle of Higher Education.* https://www.chronicle.com/article/how-will-artificial-intelligence-change-higher-ed

Selznick, B. S., & Titareva, T. (2022) Postsecondary Administrative Leadership and Educational AI: An ethical shared approach. In F. Almaraz-Menéndez, A. Maz-Machado, C. López-Esteban, & C. Almaraz-López (Ed.) *Strategy, Policy, Practice, and Governance for AI in Higher Education Institutions*, 73-100. IGI Global. https://doi.org/10.4018/978-1-7998-9247-2.ch004

Selwyn, N. (2016). *Is technology good for education?*. John Wiley & Sons.

Shannon, C. E. (1950). XXII. Programming a computer for playing chess. *The London, Edinburgh, and Dublin Philosophical Magazine and Journal of Science*, *41*(314), 256-275. https://doi.org/10.1080/14786445008521796

Shaw, L. H., & Gant, L. M. (2002). Users Divided? Exploring the Gender Gap in Internet Use. *Cyberpsychology & Behavior*, *5*(6), 517–527. https://doi.org/10.1089/109493102321018150

Shukla, P., Wilson, H. J., Alter, A., & Lavieri, D. (2017). Machine reengineering: robots and people working smarter together. *Strategy & Leadership*, *45*(6), 50-54. https://doi.org/10.1108/sl-09-2017-0089

Siau, K. (2017). Impact of artificial intelligence, robotics, and automation on higher education. In *23rd Americas Conference on Information Systems (AMCIS 2017)*. Association for Information Systems (AIS).

Silva, B., Reis, A., Sousa, J., Pires, E. S., & Barroso, J. (2022). Enhancing higher education tutoring with artificial intelligence inference. In *EDULEARN22 Proceedings*. 1609-1613. IATED. https://doi.org/10.21125/edulearn.2022.0426

Sinkovics, R. R., Stöttinger, B., Schlegelmilch, B. B., & Ram, S. (2002). Reluctance to use technology-related products: Development of a technophobia scale: Reluctance to Use Technology-Related Products. *Thunderbird International Business Review*, *44*(4), 477–494. https://doi.org/10.1002/tie.10033

Smalley, S. (2022, February 21). A Data Collection Project at GW Leads to Privacy Questions. *Inside Higher Ed*. https://www.insidehighered.com/news/2022/02/22/gw-data-collection-effort-sparks-campus-privacy-concerns

Society for Learning Analytics Research . (2023). What is Learning Analytics? *SOLAR*. https://www.solaresearch.org/about/what-is-learning-analytics/

Southgate, E. (2020). Artificial intelligence, ethics, equity and higher education: A ‘beginning-of-the-discussion’ paper. *National Centre for Student Equity in Higher Education, Curtin University, and the University of Newcastle*. https://www.ncsehe.edu.au/wp-content/uploads/2020/07/Southgate_AI-Equity-Higher-Education_FINAL.pdf

Steinour, D., Ravishanker, R., Basgen, B., Scozzafava, S., & Srinivas, K. (2018). Becoming institutional partners and brokers: The new role for IT. *EDUCAUSE Review*. https://er.educause.edu/articles/2018/7/becoming-institutional-partners-and-brokers-the-new-role-for-it

Sweeney, M., Lester, J., & Rangwala, H. (2015). Next-term student grade prediction. *2015 IEEE International Conference on Big Data (Big Data)*. Washington, DC: IEEE Computer Society, 970–975. https://doi.org/10.1109/bigdata.2015.7363847

Tan, S. C. (2010). School technology leadership: Lessons from empirical research. Paper presented at the *Australasian Society for Computers in Learning in Tertiary Education (ASCILITE) Conference*, Sydney, Australia. https://repository.nie.edu.sg/handle/10497/4622

Tarhini, A., Hone, K., & Liu, X. (2014). The effects of individual differences on e-learning users' behaviour in developing countries: A structural equation model. *Computers in Human Behavior*, *41*, 153–163. https://doi.org/10.1016/j.chb.2014.09.020

Tedx SanFrancisco (2016). A teaching assistant named Jill Watson | Ashok Goel. *Youtube*. https://www.youtube.com/watch?v=WbCguICyfTA&t=1s

Teo, T., & Van Schaik, P. (2012). Understanding the Intention to Use Technology by Preservice Teachers: An Empirical Test of Competing Theoretical Models. *International Journal of Human-Computer Interaction*, *28*(3), 178–188. https://doi.org/10.1080/10447318.2011.581892

Thelin, J. R. (2019). *A History of American Higher Education* (3rd Ed.). Baltimore, MD: Johns Hopkins University Press. https://doi.org/10.56021/9781421428826

The International Society for Technology in Education (2018). *ISTE Standards for Education Leaders*. https://iste.org/standards/education-leaders

Tinto, V. (2006). Research and Practice of Student Retention: What Next? *Journal of College Student Retention: Research, Theory & Practice*, *8*(1), 1–19. https://doi.org/10.2190/4YNU-4TMB-22DJ-AN4W

Toyama, K. (2015). *Geek Heresy: Rescuing Social Change from the Cult of Technology*. PublicAffairs. https://geekheresy.org/

Titareva, T. (2021, February). Leadership in an Artificial Intelligence Era. *Leading Change Conference*, Harrisonburg, VA, USA. https://commons.lib.jmu.edu/cgi/viewcontent.cgi?article=1012&context=leadcc

Tsai, Y. S., & Gašević, D. (2017). Learning analytics in higher education---challenges and policies: a review of eight learning analytics policies. In *Proceedings of the Seventh International Learning Analytics & Knowledge Conference*, 233-242. https://doi.org/10.1145/3027385.3027400

Tsai, Y.-S., Moreno-Marcos, P. M., Jivet, I., Scheffel, M., Tammets, K., Kollom, K., & Gašević, D. (2018). The SHEILA Framework: Informing Institutional Strategies and Policy Processes of Learning Analytics. *Journal of Learning Analytics*, *5*(3), 5–20. https://doi.org/10.18608/jla.2018.53.2

Tsai, Y.-S., Poquet, O., Gašević, D., Dawson, S., & Pardo, A. (2019). Complexity leadership in learning analytics: Drivers, challenges and opportunities. *British Journal of Educational Technology*, *50*(6), 2839–2854. https://doi.org/10.1111/bjet.12846

Tsikriktsis, N. (2004). A Technology Readiness-Based Taxonomy of Customers: A Replication and Extension. *Journal of Service Research: JSR*, *7*(1), 42–52. https://doi.org/10.1177/1094670504266132

UNESCO. (2019). Beijing consensus on artificial intelligence and education.

United Nations Educational, Scientific and Cultural Organization. Paris, France. https://unesdoc.unesco.org/ark:/48223/pf0000368303

UNESCO IESALC (2023). Harnessing the Era of Artificial Intelligence in Higher Education. A Primer for Higher Education Stakeholders. *United Nations Educational, Scientific and Cultural Organization,* Paris, France and *the UNESCO International Institute for Higher Education in Latin America and the Caribbean (IESALC)*, Caracas, Venezuela. https://unesdoc.unesco.org/ark:/48223/pf0000386670

University of Toronto (2023). *ChatGPT and Generative AI in the Classroom*. https://www.viceprovostundergrad.utoronto.ca/strategic-priorities/digital-learning/special-initiative-artificial-intelligence/

University of Washington (2006). *History of Artificial Intelligence*. https://courses.cs.washington.edu/courses/csep590/06au/projects/history-ai.pdf

U.S. Department of Education, Office of Educational Technology (2023). *Artificial Intelligence And Future of Teaching and Learning: Insights and Recommendations*. Washington, DC. https://www2.ed.gov/documents/ai-report/ai-report.pdf

U.S. Department of Education. (1982). Television and Behavior. Ten Years of Scientific Progress and Implications for the Eighties. In *US Department of Health and Human Services*.

Venkatesh, V., & Morris, M. G. (2000). Why Don't Men Ever Stop to Ask for Directions? Gender, Social Influence, and Their Role in Technology Acceptance and Usage Behavior. *MIS Quarterly*, *24*(1), 115–139. https://doi.org/10.2307/3250981

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a Unified View. *MIS Quarterly*, *27*(3), 425–478. https://doi.org/10.2307/30036540

Viberg, O., Hatakka, M., Bälter, O., & Mavroudi, A. (2018). The current landscape of learning analytics in higher education. *Computers in Human Behavior*, *89*, 98–110. https://doi.org/10.1016/j.chb.2018.07.027

Wahdain, E. A., & Ahmad, M. N. (2014). User acceptance of information technology: Factors, theories and applications. *Journal of Information Systems Research and Innovation*, *6*(1), 17–25.

Wallace, M., O'Reilly, D., Morris, J., & Deem, R. (2011). Public Service Leaders as "Change Agents" - for Whom?: Responses to leadership development provision in England. *Public Management Review*, *13*(1), 65–93. https://doi.org/10.1080/14719037.2010.501614

Webster, M.D. (2017). Philosophy of technology assumptions in educational technology leadership. *Journal of Educational Technology & Society*, *20*(1), 25–36.

Weitzman, T. (2023, March). GPT-4 Released: What It Means For The Future Of Your Business. *Forbes*. https://www.forbes.com/sites/forbesbusinesscouncil/2023/03/28/gpt-4-released-what-it-means-for-the-future-of-your-business/?sh=6be9a03e2dc6

World Economic Forum (2020, October 26). Don't fear AI. It will lead to long-term job growth. *WEF*. https://www.weforum.org/agenda/2020/10/dont-fear-ai-it-will-lead-to-long-term-job-growth/

WSJ Podcasts (2023, November 3). Microsoft's Brad Smith Wants an AI 'Off Switch. *The Wall Street Journal, What's News*. https://www.wsj.com/podcasts/whats-news/microsofts-brad-smith-wants-an-ai-off-switch/7a5e0ff5-0fe2-4ddd-b40d-9067b554b2d6

Yang, S., & Bai, H. (2020). The integration design of artificial intelligence and normal students' Education. *Journal of Physics, Conference Series*, *1453*(1), 12090–. https://doi.org/10.1088/1742-6596/1453/1/012090

Yee, D. L. (2000). Images of school principals' information and communications technology leadership. *Journal of Information Technology for Teacher Education*, *9*(3), 287-302. https://doi.org/10.1080/14759390000200097

Yi, M. Y., & Hwang, Y. (2003). Predicting the use of web-based information systems: Self-efficacy, enjoyment, learning goal orientation, and the technology acceptance model. *International Journal of Human-Computer Studies, 59*, 431-449. doi:10.1016/S1071-5819(03)00114-9

Yuting, Z., Adams, D., & Lee, K. C. S. (2022). The relationship between technology leadership and teacher ICT competency in higher education. *Education and Information Technologies*, 1-23. https://doi.org/10.1007/s10639-022-11037-0

Zawacki-Richter, O., Marín, V., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(1), 1–27. https://doi.org/10.1186/s41239-019-0171-0