FLORIDA INTERNATIONAL UNIVERSITY

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# ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION: COLLEGE STUDENTS' AI ANXIETY AS A MODERATING FACTOR IN TECHNOLOGICAL ADAPTATION

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DOCTOR OF BUSINESS ADMINISTRATION

by

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To: Dean William G. Hardin
College of Business

This dissertation, written by Jessica Kizorek, and entitled Artificial Intelligence in Higher Education: American College Students' AI Anxiety as a Moderating Factor in Technological Adaptation, having been approved in respect to style and intellectual content, is referred to you for judgment.

We have read this dissertation and recommend that it be approved.

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The dissertation of Jessica Kizorek is approved.

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Florida International University, 2025

DEDICATION

To Dr. Moses Shumow, for igniting my love affair with FIU.

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ABSTRACT OF THE DISSERTATION

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by

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Professor Fred O. Walumbwa, Major Professor

The integration of artificial intelligence (AI) into educational settings presents both significant opportunities and profound challenges. As generative AI tools become more embedded in educational practices, the need to monitor negative impacts on mental health has arisen.

While AI technologies promise to revolutionize educational experiences, they also evoke fear in students related to privacy, ethics, and future employability. This research focuses on the dual aspects of AI in education - its potential to enhance learning and its ability to induce anxiety. By understanding these dynamics, this study aims to offer insights into how educational policies and AI tool designs can be optimized to reduce anxiety and enhance positive student experiences.

The study leverages quantitative analyses to explore how AI anxiety interacts with factors like perceived behavioral control, social norms, and personal attitudes towards AI usage. Preliminary findings suggest that while students recognize the benefits of AI, their anxieties could significantly shape their behavioral intentions and actual usage patterns. With responses from 400 survey participants, advanced statistical techniques such as regression analysis and structural equation modeling were applied to assess the relationships between these variables.

Using Ajzen's 1991 Theory of Planned Behavior as a framework, the study found that students' attitudes, subjective norms, and perceived behavioral control each had a positive and significant effect on their intention to use AI tools. Additionally, behavioral intention significantly predicted actual use of AI. By combining a well-established behavioral theory with a lens on mental health, this dissertation opens the door to deeper inquiry and future research on how psychological factors shape the newest wave of technological adaptation.

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# CHAPTER I - INTRODUCTION

The emergence of generative artificial intelligence tools presents a significant shift in the landscape of education, particularly for college students (Adetayo, 2024). AI technologies such as ChatGPT, DALL-E, Midjourney, Runway, Suno, and ElevenLabs now facilitate the creation of diverse media forms like text, images, audio, and videos through text-based prompts (Cheng et al., 2023). These tools offer significant opportunities for learning and content generation, broadening the scope of educational experiences (Mollick, 2024).

AI anxiety is important to investigate because it reflects the growing psychological and emotional strain individuals experience as AI becomes more integrated into daily life. This anxiety can affect decision-making, learning outcomes, and overall well-being (Bozkurt et al., 2023). This research aims to investigate the factors influencing college students' intention and actual use of generative AI in the classroom, with a particular focus on the moderating role of AI anxiety (Du Sautoy, 2019).

The importance of research like this is multifaceted. Firstly, it addresses the growing need to understand how AI technologies impact student mental health (Wang et al., 2022). As AI becomes increasingly integrated into educational settings, it is crucial to examine the emotional responses of students and develop strategies to mitigate anxieties that may hinder learning and adoption (Dai et al., 2020). Secondly, this research is not so much about teaching students AI, but rather assessing their current perceptions of and human interactions with these technologies (Roetzer, 2022). It seeks to understand the sources of their apprehensions and excitements, aiming to identify what aspects of AI induce feelings of fear or anxiety, contrasted with those that inspire a sense of empowerment. Thirdly, this research seeks to promote student confidence in using AI for educational purposes. By addressing anxieties and fostering positive experiences with AI technologies, a sense of agency and empowerment can be cultivated among students, encouraging them to embrace AI as a valuable learning tool that serves as an opportunity opposed to a threat (Tsai et al., 2020).

**Problem Statement**

The increasing integration of artificial intelligence tools in educational settings presents both opportunities and challenges for college students (Bender, 2023). Generative AI technologies offer the potential to personalize learning, enhance creativity, and improve academic performance (Adetayo, 2024). For instance, AI-powered tutoring systems can provide individualized feedback and support, while AI image and video generators can help students visualize complex concepts and create engaging multimedia projects (Bhise et al., 2022). However, the novelty and rapid evolution of these technologies also raise concerns regarding student anxiety and its impact on the adoption and ethical use of AI in the classroom.

Students' anxieties towards the capabilities of AI can influence their motivation and engagement with learning (Almaiah et al., 2022). Despite the growing presence of AI in education, limited research has explored the complex student emotions and attitudes when it comes to using AI tools in college.

## Scope of the Problem

This research focuses on undergraduate students at U.S. colleges and universities, examining the factors that influence their intention and actual use of generative AI tools for academic tasks (Celik, 2023). The study specifically investigated the moderating role of AI anxiety, exploring how this particular emotion may amplify or mitigate the relationships between students' attitudes, subjective norms, perceived behavioral control, and their intention to use AI in the classroom.

The scope of the problem with AI in education transcends personal student anxieties, delving into broader ethical implications associated with biases found in AI algorithms (Du Sautoy, 2019). These biases often stem from the lack of representation among AI developers, who are predominantly young, white, ethnically homogenous males. This can lead to AI systems that do not fully address or even recognize the nuanced realities of students from various cultural, socioeconomic, and ethnic backgrounds (Patel, 2024). There is a critical need to ensure that AI development teams are more representative of society's diversity. This involves considering biases related to race, gender, socioeconomic status, and more (Pedro et al., 2019). Addressing these issues requires a conscious effort to design AI systems that are attuned to the varied histories, knowledge bases, and life experiences of all students, aiming to empower rather than marginalize.

The potential for misuse of AI tools for academic dishonesty, such as plagiarism or cheating, presents a significant challenge for educators (Firat, 2023). It is crucial to develop strategies to detect and prevent such misuse, while simultaneously fostering a culture of AI literacy among students.

AI anxiety is distinct from other types of anxiety because it stems specifically from the uncertainty and perceived loss of control caused by interactions with artificially intelligent systems. Unlike general anxiety or even tech-related stress, AI anxiety often involves fears about job displacement, reduced cognitive effort, ethical concerns, and the blurring of human-machine boundaries.

**Significance of the Problem**

Unlike earlier tools such as calculators, computers, or the internet, which were largely seen as supplemental, generative AI systems can simulate human thought and creativity, triggering deeper fears about diminished human agency. This existential uncertainty presents issues that were not central to past tech adoptions. Additionally, because AI tools are adaptive, they provoke anticipatory anxiety and a unique sense of unpredictability that traditional tools did not elicit.

The pervasiveness of AI across industries ensures that today's college students will inevitably encounter AI technologies (Holmes & Porayska-Pomsta, 2022). With over 19.9 million students enrolled in colleges and universities across the United States, according to Holmes and Porayska-Pomsta (2022), the impact of AI on this population is far-reaching and demands careful consideration.

The rapid advancement of generative AI tools, particularly those capable of text-to-image and text-to-video generation, presents both exciting opportunities and potential threats to the mental well-being of students (Ghotbi et al., 2021). While these technologies offer the potential to enhance learning, creativity, and problem-solving skills, their novelty and evolving capabilities may also trigger anxieties and uncertainties among students. Amid these opportunities and challenges, Wang and Wang (2022) emphasize the broader societal implications of AI, stating, "The transformative effect that AI will have on the workforce fuels concerns about its ongoing development and application." Concerns about AI replacing human skills, job displacement due to automation, and the ethical implications of AI-generated content can contribute to heightened stress among students as they navigate the complexities of an AI-infused future.

Educators and administrators face the critical challenge of preparing students for the future of AI while simultaneously addressing potential mental health concerns (Li & Huang, 2020). The integration of AI into educational settings requires a nuanced understanding of student emotions and the development of strategies to mitigate these psychological experiences. Jo (2023) emphasizes the importance of tailoring AI curricula to enhance self-efficacy by stating, "AI-related curriculum design can focus on the four facets of AISE (AI Self-Efficacy). Understanding these four distinct aspects from a practical perspective will help universities segment students' AI abilities." This approach aims to refine educational strategies that address varied student capabilities in AI applications. By fostering AI literacy, promoting ethical AI practices, and providing support for students experiencing anxieties, educators can create a more inclusive and supportive learning environment that empowers students to embrace AI as a valuable tool for learning and innovation (Nazareno & Schiff, 2021).

This research is significant as it directly addresses the need for a deeper understanding of the psychological and emotional impact of AI on college students (Kim et al., 2023). By investigating the factors influencing student adoption of generative AI, this study provided valuable insights for educators, administrators, and policymakers seeking to implement AI technologies in a responsible and ethical manner that prioritizes the well-being of students.

**Research Gap**

While the potential benefits of generative AI for education are increasingly recognized, research exploring the factors influencing student adoption of these technologies, particularly within the context of the Theory of Planned Behavior (TPB), remains limited. Several studies have investigated student attitudes toward AI in education, focusing primarily on general perceptions and acceptance of AI technologies. For example, Sindermann et al. (2021) developed a scale to measure attitudes towards AI among university students, examining factors such as fear, trust, and perceived societal impact. However, these studies often lack a theoretical grounding in established behavioral models such as the TPB, which provides a comprehensive framework for understanding the interplay of attitudes, subjective norms, perceived behavioral control, and intentions (Ajzen, 2020).

Existing research on AI anxiety has focused on the general population or specific professional contexts, with less attention given to the unique anxieties experienced by college students. Wang and Wang (2022) developed and validated an AI anxiety scale, highlighting the negative impact of anxiety on motivated learning behavior. However, their study did not specifically address the moderating role of AI anxiety in the context of the TPB or explore its influence on college students' adoption of AI tools for academic purposes.

The research gap lies in the need for a theoretically grounded investigation that examines the complex interplay between AI anxiety, student attitudes, subjective norms, perceived behavioral control, and behavioral intention to use generative AI in the classroom (Ajzen, 2020). This study aims to address this gap by applying the TPB framework to the context of generative AI adoption in higher education. Specifically, this study utilizes the TPB to investigate the relative influence of attitudes, subjective norms, and perceived behavioral control on students' intention to use generative AI tools for academic tasks. This will provide a theoretical foundation for understanding the factors that drive or hinder AI adoption among college students. This research also explores how AI anxiety moderates the relationships between the TPB constructs and behavioral intentions. In so doing, this research provides valuable insights into the complex dynamics of AI adoption and the potential challenges students may face in embracing these technologies. Finally, by focusing on generative AI technologies, this study specifically investigates student adoption of generative AI tools such as ChatGPT, DALL-E, and Midjourney, which represent a significant advancement in AI capabilities and pose unique challenges and opportunities for education.

In sum, by addressing these research gaps, this study contributes to a more comprehensive understanding of student adoption of AI in higher education and inform the development of effective strategies to promote responsible and ethical AI integration in the classroom (Celik, 2023).

**Research Questions**

This study addresses the following research questions:

> What factors affect a college student's intention and actual usage of artificial intelligence in school?

This question explores the key determinants of AI adoption among college students, drawing upon established theoretical frameworks known as the Theory of Planned Behavior (TPB) (Ajzen, 2005). Factors such as attitude, subjective norms, perceived behavioral control, and AI anxiety were examined to understand their influence on students' intention and actual use of AI technologies.

> What role does anxiety play in college student adoption of generative AI to help them with schoolwork?

This question delves into the specific role of AI anxiety as a moderating factor in the adoption of generative AI tools. The study investigated how anxiety influences the relationship between students' attitudes, subjective norms, perceived behavioral control, and their intention to use AI for academic purposes (Dinc, 2023).

# CHAPTER II - LITERATURE REVIEW

The rapid advancement and integration of artificial intelligence technologies in various aspects of society have prompted growing interest in understanding their impact on education, particularly for college students (Chen et al., 2020). This literature review explores existing research on AI in education, with a specific focus on student adoption of generative AI tools and the moderating role of AI anxiety within the framework of the Theory of Planned Behavior (TPB) (Ajzen, 2011).

According to Merceron et al. (2015), in recent years applications of big data and AI in education have made significant headway. This highlights a novel trend in leading-edge educational research. The convenience and embeddedness of data collection within educational technologies, paired with computational techniques, have made the analysis of big data a reality. The key research trends in the domains of big data and AI are associated with assessment, individualized learning, and precision education (Roetzer, 2022). Model-driven data analytics approaches will grow quickly to guide the development, interpretation, and validation of the algorithms (Dinc, 2023). However, conclusions from educational analytics should be applied with caution (Du Sautoy, 2019). At the education policy level, the government should be devoted to supporting lifelong learning, offering teacher education programs, and protecting personal data collected from users by the AI's large language models (Adetayo, 2024). Students are providing AI chatbots with far more sensitive, personal, and even legal data then they would have ever provided, for instance, to a social media platform like Facebook or Instagram. However, they may not fully grasp the long-term implications of the data they are sharing, which can be used in the future in ways they have not yet anticipated (Mollick, 2024).

### Artificial Intelligence and Education

AI has emerged as a transformative force in education, offering numerous opportunities to personalize learning, enhance teaching methodologies, and improve student outcomes (Bates et al., 2020). This literature review investigates students' perceptions of creating AI text, image, or video through a quantitative descriptive study. Studies have explored the application of AI in various educational contexts (Chen et al., 2020), including: Intelligent tutoring systems (Graesser et al., 2012), automated grading, customized feedback, student retention, and dropout prediction models (Rovira et al., 2017). Recent advancements in generative AI, exemplified by tools like ChatGPT and DALL-E, have significantly broadened the scope of AI applications in education (Motlagh et al., 2023). These tools leverage sophisticated algorithms to generate diverse forms of media content in response to text-based prompts. By harnessing these technologies, students gain access to a wide array of interactive learning experiences. They can use these tools to explore complex concepts visually, interact with content in novel ways, and express their creativity through various media formats. These advancements offer students unprecedented opportunities to engage with educational materials and enhance their individual learning outcomes (Adetayo, 2024).

AI-driven platforms adapt tasks to individual student needs and learning preferences, enhancing personalized education (Mollick, 2024). Recent integrations include AI with augmented reality (AR), virtual reality (VR), and mixed reality (MR) technologies, which track and adjust to students' needs in real-time (Chiu et al., 2023). Notably, virtual patients and intelligent virtual laboratories offer medical students immersive, interactive learning experiences, complete with real-time feedback and tasks tailored to varying skill levels (Kong et al., 2021). These innovations significantly improve the learning environment by providing customized educational experiences and support to future medical doctors, amongst other student groups (Chiu et al., 2023).

## The Theory of Planned Behavior

The Theory of Planned Behavior (TPB), introduced by Ajzen in 1991, offers a robust framework for comprehending and predicting human behavior across diverse contexts (Ajzen 1991). TPB posits that an individual's intention to engage in a specific behavior is influenced by three primary factors: attitude towards the behavior, subjective norms, and perceived behavioral control (Ajzen, 2005). Attitude reflects the individual's overall evaluation of the behavior, encompassing perceived benefits and drawbacks (Peng, 2023). Positive attitudes increase the likelihood of intention to engage in the behavior, while negative attitudes have the opposite effect. Subjective norms represent the perceived social pressures or expectations regarding the behavior from significant others.

Individuals are more inclined to intend to perform a behavior if they perceive social approval or encouragement, and vice versa (Ajzen, 1980, 2006, 2012, 2015, 2020). Perceived behavioral control refers to an individual's belief in their ability to successfully execute the behavior. Higher perceived control indicates greater confidence in overcoming obstacles, thus increasing the likelihood of intention (Ajzen et al., 2011).

Together, these components shape an individual's behavioral intention, which predicts actual behavior (Sanusi et al., 2024). TPB has found widespread application in fields like psychology, health behavior, and technology adoption, providing insights into the determinants of human behavior and informing interventions to promote desirable outcomes (Kim, 2002). In the realm of technology adoption, TPB aids in understanding users' intentions towards adopting new technologies, guiding the development of effective strategies for behavior change and technology adoption (Dinc, 2023).

**College Student Technological Adaptation**

Technological adaptation among college students is akin to historical adaptation of the internet and social media, which served as precursors to this newest wave of technology (Pedro et al., 2019). The introduction of the internet revolutionized access to information and learning methodologies, compelling students to develop new skills for navigating digital spaces effectively. Similarly, the emergence of social media redefined communication dynamics, necessitating an understanding of digital interaction and personal branding (Du Sautoy, 2019). Today, AI tools are the new frontier, requiring students to further adapt by understanding and leveraging these technologies to enhance their learning experiences and prepare for AI-influenced job markets (Mollick, 2024). This continuous evolution underscores the importance of adaptability and lifelong learning in an increasingly digital world.

The challenge now is not only in mastering these tools but also in understanding their implications—both positive and negative—on personal and professional levels. As AI becomes deeply integrated into various sectors, the skills required to interact with and manage AI technologies become crucial. Education systems must, therefore, evolve not only to introduce these technologies but also to embed the critical thinking needed to navigate and innovate with them responsibly. This adaptation is not just about utilizing AI but understanding its broader impact on society and our individual roles within that context.

While research on AI in education has grown significantly in recent years, much of the existing literature focuses on the development and implementation of AI systems rather than on student adoption and user experiences. Studies of Kim et al. (2020) exploring student attitudes toward AI in education have primarily focused on general perceptions of AI technologies or on specific AI applications such as chatbots (Abdaljaleel et al., 2023). However, these studies often lack a theoretical grounding in established behavioral models like the TPB, which can provide a more nuanced understanding of the factors influencing student adoption of AI tools.

**AI Anxiety and Mental Health**

The emergence of artificial intelligence technologies has brought about significant advancements in various domains, including education, healthcare, and business. Higher education is the business in focus for this research project. Alongside its potential benefits, AI has also raised concerns about its impact on mental health, particularly regarding AI anxiety (Li & Huang 2020). AI anxiety refers to the fear or apprehension individuals may experience due to the perceived threats or uncertainties associated with AI technologies. This anxiety can stem from various factors, including concerns about job displacement, loss of privacy, and the ethical implications of AI algorithms.

Research on AI anxiety and its effects on mental health is still in its early stages but is gaining attention due to the increasing integration of AI in everyday life (Gupta et al., 2023). Studies conducted by Nazareno and Schiff (2021) have shown that individuals who perceive AI as a threat to their job security or personal privacy may experience heightened levels of anxiety and stress. The complexity and opacity of AI algorithms can contribute to feelings of powerlessness and lack of control (Kim et al., 2023).

Addressing AI anxiety and promoting mental well-being in the age of AI requires a multi-faceted approach. This includes raising awareness about the capabilities and limitations of AI, promoting digital literacy and critical thinking skills, and implementing policies and regulations to ensure the ethical and responsible use of AI technologies. Additionally, providing access to mental health resources and support networks can help individuals cope with AI-related anxiety and navigate the challenges posed by technological advancements (Alzahrani, 2023).

To effectively address AI-related anxiety and promote mental well-being, a comprehensive strategy is essential. Educating individuals about AI's potential and limitations, fostering digital literacy and critical thinking, and enforcing ethical use policies are all critical components (Mollick, 2024). Moreover, ensuring that mental health resources and support networks are accessible is vital for helping individuals manage AI-induced anxiety and the challenges arising from rapid technological changes (Alzahrani, 2023).

## Ethical Considerations

Ethical implications of AI encompass a broad spectrum of considerations regarding the moral, social, and legal dimensions of artificial intelligence technologies (Henry, 2025). As AI systems continue to permeate various aspects of society, from healthcare and finance to education and governance, understanding and addressing these ethical concerns have become paramount (Patel, 2024). One significant ethical consideration is the potential for AI algorithms to perpetuate or exacerbate biases present in the data they are trained on (du Sautoy, 2019). This can lead to discriminatory outcomes, disadvantaging certain individuals or groups based on factors such as race, gender, or socioeconomic status. Privacy and data protection are also central ethical concerns in the realm of AI. As AI systems increasingly rely on vast amounts of personal data to function effectively, questions arise about the collection, storage, and use of this data. Safeguarding individuals' privacy rights and ensuring data security are critical for maintaining public trust in AI technologies and protecting individuals' autonomy and dignity.

The ethical implications of artificial intelligence in education are multifaceted and carry significant implications for students, educators, and society as a whole (Pedro et al., 2019). One primary concern revolves around fairness and bias in AI systems used for educational purposes. These systems may inadvertently perpetuate or amplify existing inequalities in access to educational opportunities and resources, particularly if they are trained on biased data sets or programmed with biased algorithms. Ensuring fairness and equity in AI-driven educational technologies is crucial for promoting equal access to quality education for all students, regardless of their background or circumstances (Holmes & Porayska-Pomsta, 2022). Educational AI systems often collect and process large amounts of personal data from students, raising concerns about data privacy, security, and consent. Safeguarding students' sensitive information and ensuring compliance with data protection regulations are essential for upholding their rights to privacy and autonomy within educational settings.

The ethical implications of AI in education are a crucial aspect of this research. Concerns regarding potential biases in AI algorithms, data privacy and security, and the potential for misuse of AI tools for academic dishonesty require careful consideration (Ghotbi et al., 2021). Safety and security considerations also come into play when discussing the ethical implications of AI in education. Ensuring the safety and well-being of students when using AI-driven educational technologies, such as online learning platforms or AI-powered tutoring systems, is paramount. Educators and policymakers must prioritize the development and implementation of comprehensive safety measures to protect students from potential risks, including data breaches, cyberattacks, and harmful content (Lim et al., 2023). "Understanding employees' AISE (AI self-efficacy) can assist companies in promoting AI schemes" (Wang & Chuang, 2023).

In this politically sensitive era, understanding the intersection between AI, student rights, and free speech is becoming increasingly critical (McNeal, 2025). Recent political shifts have underscored the need for educational institutions to foster an environment where students can apply a critical human filter to the advice dispensed by AI chatbots. This is especially pertinent as AI systems do not inherently understand the nuances of free speech and the consequences of its breach, particularly under stringent policies affecting non-citizen students. For instance, the alarming trend of international students facing severe penalties for their legally protected speech, such as visa revocations or deportations, signals a crucial juncture for educational policies (Henry, 2025). By emphasizing the importance of prudent AI engagement and educating students on safeguarding themselves against potential legal and ethical pitfalls, universities can help protect the exchange of ideas while ensuring adherence to evolving national policies (McNeal, 2025). The recent urgent alerts from national journalism organizations exemplify the growing need for a reevaluation of how student media navigates these complexities, highlighting the delicate balance between ethical journalism and minimizing harm in new political landscapes (Henry, 2025).

It is essential to develop ethical guidelines and policies that ensure responsible AI implementation and address potential risks to student privacy and equity (Pedro et al., 2019). Establishing ethical guidelines, standards, and best practices for the responsible use of AI in education is essential for mitigating risks, promoting fairness and equity, and ensuring that AI technologies contribute positively to the enhancement of teaching and learning experiences for all students (Holmes & Porayska-Pomsta, 2022).

## Measurement Instruments

Measurement instruments for AI in education refer to tools or scales designed to assess various aspects related to the integration, perception, and impact of artificial intelligence in educational settings (Celik, 2023). These instruments are developed to gather data on students' attitudes, beliefs, behaviors, and experiences concerning AI technology in education. Researchers have yet to fully utilize such instruments to measure constructs like students' perceptions of AI, their anxiety towards AI, their acceptance of AI-based learning tools, and their intentions to use or adopt AI technology in educational contexts.

These measurement instruments are crucial for researchers seeking to understand the attitudes and behaviors of students towards AI in education. By employing validated scales or tools, researchers could collect quantitative data to examine the effectiveness of AI interventions, the acceptance of AI-powered educational systems, and the factors influencing students' attitudes and behaviors towards AI technology. Additionally, these instruments could contribute to the development of evidence-based practices and policies for the ethical and effective integration of AI in education.

Several studies have developed and validated instruments to measure constructs relevant to this research. Cheng et al. (2023) designed a scale to assess undergraduate students' conceptions of AI in education, while Wang and Wang (2022) developed an AI anxiety scale. These instruments, along with established measures of TPB constructs (Francis et al., 2010), provide a foundation for developing a comprehensive survey instrument to investigate student adoption of generative AI and the moderating role of AI anxiety.

## Theoretical Foundation and Constructs

Introduced by Ajzen in 1991, the Theory of Planned Behavior (TPB) serves as a cornerstone for understanding human behavior across diverse contexts, including the adoption of new technologies such as artificial intelligence tools in educational settings.

Ajzen's seminal work laid the foundation for this model by proposing that an individual's behavior is primarily driven by their intention to perform that behavior (Ajzen, 1991). Over the years, the TPB has undergone rigorous empirical testing and theoretical refinement, solidifying its position as a robust and versatile framework for explaining and predicting human behavior.

Bosnjak et al. (2020) provided a comprehensive overview of recent advancements and applications of the TPB, highlighting its adaptability and relevance across diverse fields, including health behaviors, environmental actions, and educational technology adoption. Their work underscores the theory's ability to explain a wide range of human behaviors, including the complex decision-making processes involved in adopting novel technologies like AI.

**The Theory of Planned Behavior: A Foundation for Predicting Behavior**

The TPB builds upon the earlier Theory of Reasoned Action (TRA) (Ajzen & Fishbein, 1975) by incorporating the crucial element of perceived behavioral control (PBC; Madden, 1992). According to the TPB, an individual's intention to engage in a particular behavior is influenced by three key factors:

*Attitude.* This refers to an individual's positive or negative evaluation of performing the behavior. These evaluations are shaped by beliefs about the consequences of the behavior and the individual's assessment of those potential outcomes (Eagly, 1991). In the context of AI adoption, students with positive attitudes towards AI are more likely to believe that using AI tools will enhance their learning, creativity, and academic performance.

*Subjective Norms.* This factor reflects the perceived social pressure to perform or not perform the behavior. It is influenced by an individual's perception of what important others (e.g., peers, instructors, family) think about the behavior and their motivation to comply with those perceived expectations (Mathieson, 1991). For college students, subjective norms may involve perceptions of whether their peers and instructors encourage or discourage the use of AI tools in the classroom.

*Perceived Behavioral Control.* This refers to an individual's perception of the ease or difficulty of performing the behavior. It is influenced by beliefs about the presence of factors that may facilitate or hinder behavior performance, such as access to resources, skills, and opportunities (Ajzen, 1991). Students with higher PBC regarding AI are more likely to believe they have the necessary skills and resources to use AI tools effectively for academic tasks.

The interplay of these three factors shapes an individual's intention, which is considered the most proximal determinant of actual behavior.

**Applying TPB to AI Adoption in Higher Education**

The TPB has been successfully applied to investigate technology adoption in various educational contexts. Kim (2002) employed the TPB to examine teachers' intentions to use the internet, highlighting the importance of attitudes, subjective norms, and PBC in shaping technology adoption behavior among educators. Similarly, Sanusi et al. (2024) investigated the factors influencing pre-service teachers' intentions to use AI, demonstrating the relevance of the TPB in understanding AI adoption in teacher education programs.

**Role of Anxiety in Technology Adoption**

Technological anxiety, characterized by apprehension or fear of new technologies, can significantly impact adoption behaviors. Mokyr (2015) traced the history of technological anxiety back to the Industrial Revolution, noting concerns about job displacement and the dehumanizing effects of machines. These anxieties persist today, particularly with the rise of automation, robotics, and AI (Chiarini, 2023). “AI Anxiety,” as termed by Johnson and Verdicchio (2017), refers specifically to the fear that AI may spiral out of control and pose existential threats to humanity.

In the context of AI adoption in education, anxiety may manifest as concerns about AI replacing human creativity and ingenuity, job displacement due to automation, and the ethical implications of AI-generated content. These anxieties can significantly impact students’ attitudes, subjective norms, and PBC, ultimately influencing their willingness to adopt and use AI tools in their academic work.

# CHAPTER III - METHODOLOGY

## Measurement Model

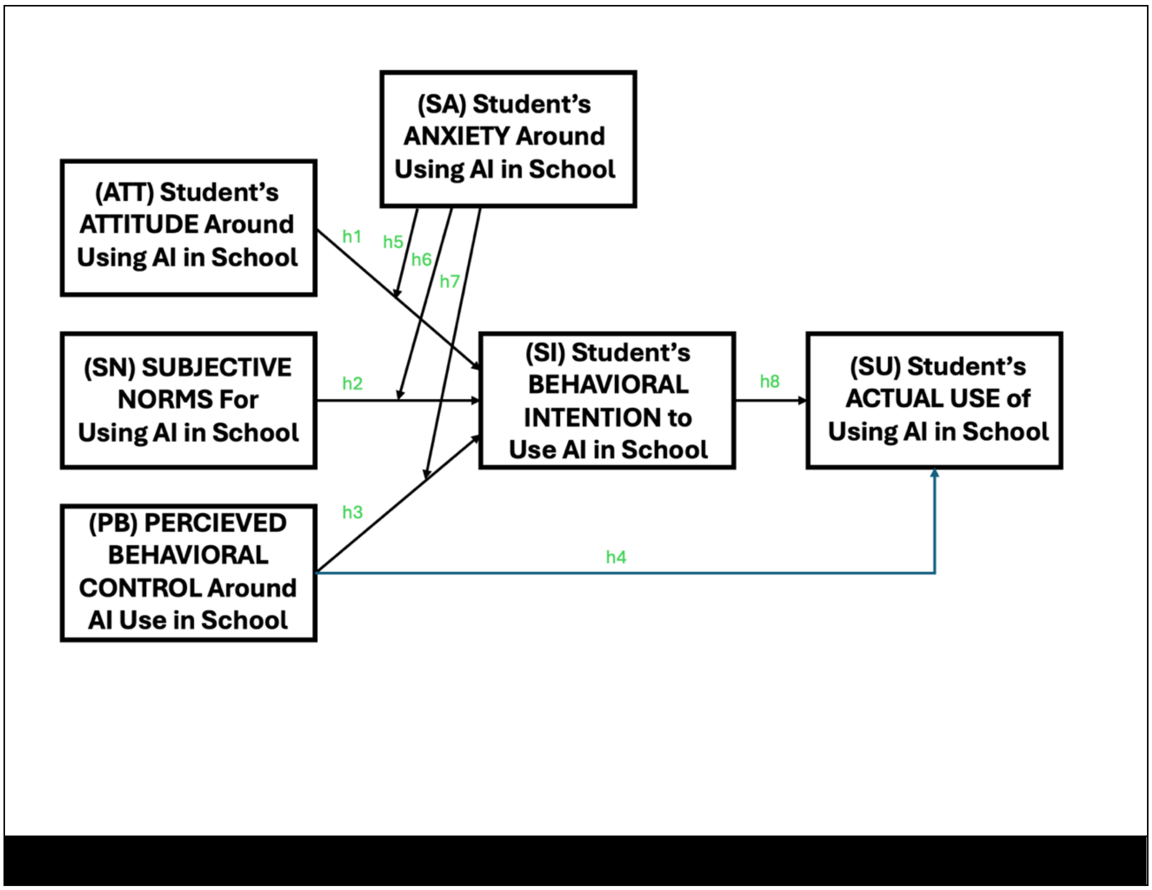

**Table 1 – Summary of Hypotheses**

| | Hypotheses | Reference |
|---|---|---|
| H1+ | As students' attitudes towards AI become positive, their behavioral intention towards the use of AI will increase. | (Ajzen, 1991) |
| H2+ | As students' subjective norms towards AI become positive, their behavioral intention towards the use of AI will increase. | (Ajzen, 1991) |
| H3+ | As students' perceived behavioral control towards AI become positive, their behavioral intention towards the use of AI will increase. | (Ajzen, 1991) |
| H4+ | As students' perceived behavioral control towards AI become positive, their actual use of AI will increase. | (Ajzen, 1991) |
| H5- | A college student's AI anxiety will moderate the relationship between attitude and intent to use AI in school, such that as anxiety increases, the relationship between attitude and intent weakens. | (Huang, 2002; Tsai, 2020) |
| H6- | A college student's AI anxiety will moderate the relationship between subjective norms and intent to use AI in school, such that as anxiety increases, the relationship between subjective norms and intent weakens. | (Huang, 2002; Tsai, 2020)) |
| H7- | A college student's AI ANXIETY will moderate the relationship between perceived behavioral control and intent, such that as anxiety increases, the relationship between perceived behavioral control and intent weakens. | (Huang, 2002; Tsai, 2020) |
| H8+ | As students' behavioral intent towards AI (SI) becomes positive, their actual use of AI (SU) will increase. | (Ajzen, 1991) |
| H9+ | Behavioral Intent (SI) mediates a relationship between Students Attitude (AT) and Actual Use of AI (SU) in school. | (Ajzen, 1991) |
| H10+ | Behavioral Intent (SI) mediates a relationship between Subjective Norms (SN) and Actual Use of AI (SU) in school. | (Ajzen, 1991) |
| H11+ | Behavioral Intent (SI) mediates a relationship between Perceived Behavioral Control (PB) and Actual Use of AI (SU) in school. | (Ajzen, 1991) |

## Construct Definitions

**Table 2 - Construct Definitions**

| Construct | Definition | Reference |
|---|---|---|
| Social Norms of AI Use (SN) | The degree to which students perceive influential people support the use of AI. | (Ajzen, 1991) |
| Perceived Behavioral Control of AI (PB) | An individual's belief that they have the ability to use AI effectively. | (Ajzen, 1991) |
| Attitude Toward AI Use (AT) | An individual's overall evaluation of AI use. | (Ajzen, 1991) |
| AI Anxiety (SA) | The apprehension and feelings of unease experienced by individuals as they adopt and learn new AI tools. | (Meuter, 2003; Johnson, 2017; Wang, 2022) |
| Actual Use of AI for School (SU) | An individual's level of familiarity, exposure, and interaction with AI. | (Venkatesh, 2012) |
| Intention to Use AI (SI) | An individual's readiness and conscious plan to use AI. | (Ajzen, 1991; Venkatesh, 2003) |

## Hypotheses Justifications

This section provides justifications for the proposed hypotheses based on the TPB and relevant research on AI adoption and anxiety in educational settings.

Hypothesis 1 states that as students' attitudes towards AI become positive, their behavioral intention towards the use of AI will increase. This hypothesis aligns with the core principle of the TPB that attitude is a primary determinant of behavioral intention (Ajzen, 1991). Students with positive attitudes towards AI are more likely to perceive its benefits for learning, creativity, and academic performance, leading to a stronger intention to use AI tools in the classroom. Studies on student perceptions of AI in education have indicated a generally positive attitude towards AI-powered learning tools and their potential to enhance the learning experience (Chai et al., 2021; Haryanto & Ali, 2019).

Hypothesis 2 suggests that as students’ subjective norms towards AI become positive, their behavioral intention towards the use of AI will increase. Subjective norms, reflecting the perceived social pressure to engage in a behavior, play a significant role in shaping behavioral intentions (Ajzen, 1991). In the context of AI adoption, students who perceive that their peers and instructors support and encourage the use of AI tools are more likely to develop a stronger intention to use them for academic purposes. Research on technology adoption in education has demonstrated the influence of subjective norms on student behavior (Kim, 2002; Sanusi et al., 2024).

Hypothesis 3 suggests that as students’ perceived behavioral control towards AI become positive, their behavioral intention towards the use of AI will increase. PBC, reflecting the belief in one's ability to perform a behavior, is a crucial determinant of behavioral intention within the TPB framework (Ajzen, 1991). Students who feel confident in their ability to use AI tools effectively are more likely to develop a stronger intention to integrate them into their learning practices. Research on technology adoption has consistently shown a positive relationship between PBC and intention to use new technologies (Levy & Ben-Ari, 2008). H4 suggests that as students perceived behavioral control towards AI become positive, their actual use of AI will increase.

PBC not only influences behavioral intention but can also directly impact actual behavior. Students who believe they have the necessary skills and resources to use AI tools effectively are more likely to overcome potential barriers and actually use these tools in their academic work. This aligns with the TPB's proposition that PBC, along with intention, can directly predict behavior, especially when it reflects actual control over the behavior (Ajzen, 1988).

Hypothesis 5 posits that a college student’s AI anxiety will moderate the relationship between attitude and intent to use AI in school, such that as anxiety increases, the relationship between attitude and intent weakens. AI anxiety, stemming from concerns about the implications of AI technology, can negatively impact students' attitudes and intentions towards using AI tools. As anxiety levels increase, students may become more apprehensive about the potential risks and uncertainties associated with AI, leading to a decline in their positive attitudes and, consequently, a weaker intention to use AI in their academic work. "Individuals with low AISE (AI self-efficacy) may perceive using AI technologies/products...as more complicated and stressful" (Wang & Chuang, 2023).

Hypothesis 6 posits that a college student’s AI anxiety will moderate the relationship between subjective norms and intent to use AI in school, such that as anxiety increases, the relationship between subjective norms and intent weakens. Similar to its moderating effect on the attitude-intention relationship, AI anxiety may also weaken the influence of subjective norms on behavioral intention. As anxiety levels rise, students may become less receptive to the social pressures and expectations surrounding AI use, prioritizing their concerns and apprehensions over the opinions of others.

Hypothesis 7 suggests that a college student's AI anxiety will moderate the relationship between perceived behavioral control and intent, such that as anxiety increases, the relationship between perceived behavioral control and intent weakens. AI anxiety can also moderate the relationship between PBC and behavioral intention. Students experiencing high levels of anxiety may doubt their ability to use AI tools effectively, despite possessing the necessary skills or resources. This apprehension can diminish their perceived control and weaken the positive influence of PBC on their intention to use AI.

Hypothesis 8 states that as students' behavioral intent towards AI becomes positive, their actual use of AI will increase. This hypothesis reflects the TPB's core proposition that behavioral intention is the immediate antecedent of behavior (Ajzen, 1991). Students with a stronger intention to use AI for academic purposes are more likely to actively seek opportunities to integrate these tools into their learning practices and overcome potential barriers to adoption.

Hypothesis 9 suggests that behavioral Intent (BI) mediates a relationship between Students Attitude (AT) and Actual Use of AI (AU) in school. This hypothesis suggests that students' attitudes towards AI influence their behavioral intent, which in turn affects their actual use of AI. According to the TPB, behavioral intention serves as a key mediator between attitudes and behavior (Ajzen, 1991). When students have a positive attitude towards AI, they are more likely to form a strong intention to use it, which then translates into actual usage. Research on technology acceptance has shown that behavioral intention is a critical link between attitudes and actual behavior, particularly in educational settings (Venkatesh et al., 2003; Davis, 1989).

Hypothesis 10 states that behavioral Intent (BI) mediates a relationship between Subjective Norms (SN) and Actual Use of AI (AU) in school. This hypothesis asserts that the influence of subjective norms on actual AI use is mediated by behavioral intention. Within the TPB framework, subjective norms shape behavioral intentions by reflecting the perceived social pressure to perform a behavior (Ajzen, 1991). Students who perceive that their peers and instructors support the use of AI are more likely to develop a strong intention to use it, which subsequently leads to actual usage. Empirical studies have demonstrated that subjective norms significantly impact behavioral intention, which in turn influences actual behavior (Taylor & Todd, 1995; Venkatesh & Davis, 2000).

Hypothesis 11 suggests that behavioral Intent (BI) mediates a relationship between Perceived Behavioral Control (PBC) and Actual Use of AI (AU) in school. This hypothesis indicates that perceived behavioral control affects actual AI use through its impact on behavioral intention. The TPB asserts that PBC directly influences both behavioral intention and actual behavior (Ajzen, 1991). When students believe they have the ability to use AI tools effectively, they are more likely to form a strong intention to use them, leading to actual usage. Research on technology adoption has consistently shown that PBC is a significant predictor of behavioral intention, which in turn predicts actual use (Mathieson, 1991; Taylor & Todd, 1995).

## Research Design

To investigate the factors influencing college students' adoption of generative AI tools in the classroom and the moderating role of AI anxiety, this study employed quantitative research methodology. A descriptive approach using deductive reasoning was applied, utilizing a cross-sectional survey design.

## Participants and Sampling

The target population for this study consisted of students enrolled in U.S. colleges and universities, representing diverse academic disciplines and backgrounds. A sample size of 400 students was recruited through CloudResearch, an online platform providing access to a large pool of potential participants. A simple random sampling method was employed to ensure representativeness and minimize selection bias. The target population was college students in the United States, regardless of ethnicity.

## Data Collection Instrument

A structured questionnaire was developed to collect data on the following constructs:

*Attitude* (ATT): Students' positive or negative evaluation of using AI in the classroom.

*Subjective Norms* (SN): Students' perception of the social pressure to use or not use AI in the classroom.

*Perceived Behavioral Control* (PBC): Students' belief in their ability to use AI effectively for academic tasks.

*AI Anxiety* (AA): Students' level of apprehension or fear related to using AI technologies.

*Behavioral Intention* (BI): Students' intention to use or not use AI for academic purposes.

*Actual Use of AI* (AU): The extent to which students actually use AI tools in their academic work.

The questionnaire included established measures of TPB constructs (Francis et al., 2010), AI anxiety (Wang & Wang, 2022), and items specifically designed to assess student perceptions of generative AI in education. At the beginning survey participants entered demographic information. On the core questionnaire, a seven-point Likert scale was used to measure the constructs, ranging from (1) "Strongly Disagree" to (7) "Strongly Agree." Then at the end, research subjects answered two open-ended questions that might be coded and analyzed from a qualitative perspective in future research.

**Data Collection Technique**

Upon obtaining Institutional Review Board (IRB) approval, the survey was distributed online through CloudResearch. Participants were provided an informed consent form outlining the study's purpose, procedures, risks, and benefits of participation. Anonymity was ensured, and participants had the right to withdraw from the study at any time.

## Data Analysis

The collected data was analyzed using the statistical software called SPSS, which was used to summarize the respondents' characteristics and provide an overview of the data. Inferential statistics, including correlation analysis, multiple regression, and moderation analysis, were employed to examine the relationships between the TPB constructs, AI anxiety, and behavioral intention to use generative AI. Moderation analysis specifically investigated the potential interaction effects of AI anxiety on the relationships between the TPB constructs and behavioral intention.

## Informed Pilot

An informed pilot was carried out to verify the reliability and validity of the measurement items. The participants were given a cover letter that provides an overview of the study, including the measurement model and explanations of the different groups included in the survey. These groups consisted of qualifier items, constructs, and control questions. The reviewers were also be presented with potential issues and asked to consider each one while assessing the items in the measurement instrument. Each category was accompanied by its respective definitions. The informed pilot was reviewed by eight students and colleagues from the DBA program at FIU, who were asked to provide their feedback on each item.

## Full Pilot

The final version of the measurement instrument was designed in Qualtrics XM and disseminated through CloudResearch. The survey was given to college and university students living and attending school in the United States, who could be of any race or ethnicity but had to be actively enrolled in higher education. An advertisement was created entitled “Opinions on AI Use by College Students in the United States.”

**Ethical Considerations**

This study adhered to ethical guidelines for research involving human subjects. Informed consent was obtained from all participants, and anonymity and confidentiality were maintained throughout the research process. Participants were informed of their right to withdraw from the study at any time without penalty. The study design and data collection procedures were reviewed and approved by the Institutional Review Board (IRB) before data collection commenced.

# CHAPTER IV - RESULTS

## Measurements

The measurement instrument assessed six key constructs related to college student adoption of generative AI and the moderating role of AI anxiety using a 7-point Likert scale ranging from "Strongly Disagree" (1) to "Strongly Agree" (7). The constructs included:

*Attitude toward AI use (ATT)*. This construct measured students' overall evaluation of using generative AI tools for academic purposes. Items assessed students' beliefs about the potential benefits and drawbacks of using AI for learning, creativity, and academic performance. For instance, items included:

"Using AI tools in my coursework would help me learn more effectively."

"I am concerned that using AI tools would hinder my creativity."

*Subjective norms (SN).* This construct measures students' perceptions of social pressure to use or not use AI in the classroom. Items assessed students' beliefs about whether their peers and instructors support and encourage the use of AI tools for academic tasks. Example items:

My classmates think using AI tools is helpful for learning."

"My professors discourage the use of AI tools in assignments."

*Perceived behavioral control (PBC).* This construct measures students' beliefs in their ability to use AI effectively for academic purposes. Items assessed students' self-efficacy and confidence in using AI tools for tasks such as research, writing, and problem-solving. Examples:

"I am confident that I can learn to use AI tools effectively."

"I feel comfortable using AI tools to complete my assignments."

*AI anxiety (AA).* This construct measures students' level of apprehension or fear related to using AI technologies. Items assessed students' concerns about the potential negative impacts of AI, such as job displacement, loss of creativity, and ethical issues. Examples:

"I am worried that AI will eventually replace human workers."

"I am concerned about the ethical implications of using AI-generated content."

*Behavioral intention (BI).* This construct measures students' intention to use or not use AI for academic purposes. Items assessed students' willingness and plans to integrate AI tools into their learning practices. Examples:

"I intend to use AI tools to help me with my studies."

"I plan to avoid using AI tools in my academic work."

*Actual use of AI (AU).* This construct measures the extent to which students actually use AI tools in their academic work. Items assessed the frequency and variety of AI tools students use for tasks such as research, writing, and problem-solving. Examples:

"I regularly use AI tools to help me with my research."

"I have never used AI tools for any of my academic work."

The questionnaire items were drawn from existing validated scales and adapted to specifically address the context of generative AI adoption in higher education. The survey instrument was pilot tested with a small group of DBA graduate students to ensure clarity, comprehensiveness, and face validity before being administered to the main study sample.

**Data Analysis**

This research adopted a systematic approach to data analysis, encompassing several stages to ensure a thorough and robust examination of the collected data.

*Descriptive Statistics.* The initial stage involved descriptive statistical analysis to summarize the data and provide an overview of the sample characteristics. Measures of central tendency (e.g., mean, median) and dispersion (e.g., standard deviation, range) were calculated for each construct, providing insights into the distribution and variability of the data.

*Normality Tests*. Normality tests, such as the Shapiro-Wilk and Kolmogorov-Smirnov tests, were conducted to assess whether the data followed a normal distribution. This was crucial for determining the appropriateness of parametric statistical tests in subsequent analyses. Appropriate data transformations or non-parametric tests were considered.

*Confirmatory Factor Analysis (CFA).* CFA was employed to assess the construct validity of the measurement instrument. This involves evaluating how well the observed variables (survey items) represent the latent constructs (e.g., attitude, subjective norms, PBC, AI anxiety). The analysis examined factor loadings, model fit indices (e.g., Comparative Fit Index [CFI], Root Mean Square Error of Approximation [RMSEA], Standardized Root Mean Square Residual [SRMR]), and internal consistency reliability (e.g., Cronbach's alpha) to ensure the validity and reliability of the measurement model.

*Correlation Analysis*. Pearson correlation coefficients were calculated to examine the strength and direction of the relationships between the TPB constructs, AI anxiety, behavioral intention, and actual use of AI. This provided preliminary insights into the associations between the variables and inform subsequent analyses.

*Moderation Analysis.* Moderation analysis was conducted to investigate the potential interaction effects of AI anxiety on the relationships between the TPB constructs and behavioral intention. This involved testing whether the strength or direction of the relationships between the independent variables (attitude, subjective norms, PBC) and the dependent variable (behavioral intention) varies depending on the level of AI anxiety.

**Additional Analyses**

Further analyses were conducted including, including Multiple Regression Analysis to examine the relative contributions of the TPB constructs and AI anxiety in predicting behavioral intention and actual use of AI, Path Analysis to explore the direct and indirect effects of the variables on behavioral intention and actual use, and Comparative Analyses to investigate potential differences in AI adoption and anxiety levels across different student groups (e.g., by gender, academic major, prior experience with AI).

SPSS statistical software was used to conduct data analysis. This software package provided a wide range of statistical tools and techniques necessary for analyzing the data and testing the research hypotheses. By following these steps, this proposed research sought to provide insights into the relationships among the variables, along with the validity and reliability of the constructs to ensure a comprehensive analysis of the data.

**Demographic Information**

The demographic table (Table 3) provides insight into the composition of the sample population, highlighting key characteristics in terms of age, gender, education, and race. The majority of respondents (86.6%) are between the ages of 19 and 29, indicating a predominantly young sample, while 9.1% are 18 or younger and only 4.0% fall within the 30-39 age group. There is minimal representation for individuals aged 40 and above, with only 0.3% in the 40-49 range and none in the older categories.

In terms of gender, the sample consists primarily of females (55.3%), followed by males (38.7%), with a notable 6% identifying as nonbinary, reflecting some diversity in gender representation. Regarding educational background, the majority (63.3%) have completed high school or earned a GED. Additionally, 16.6% hold an associate degree, while 17.3% have obtained a bachelor’s degree. A smaller portion of the sample has pursued advanced education, with 2.3% earning a master’s degree and only 0.3% attaining a doctorate.

The racial composition reveals that over half of the sample identifies as White/Caucasian (54.55%), followed by Asian (26.4%) and Black/African American (16.1%). Smaller representations include American Indian or Alaska Native (2.3%) and Native Hawaiian or Other Pacific Islander (0.8%). Overall, the sample skews towards younger adults, primarily in their early careers or college years, with a varied educational background and a somewhat racially diverse composition.

**Table 3 - Demographics**

| Characteristics | Frequency | % of Sample |
|---|---|---|
| Age | | |
| 18 or younger | 36 | 9.1% |
| 19-29 | 345 | 86.6% |
| 30-39 | 16 | 4.0% |
| 40-49 | 1 | 0.3% |
| 50-59 | 0 | 0% |
| 60-69 | 0 | 0% |
| 70+ | 0 | 0% |
| Gender | | |
| Male | 154 | 38.7% |
| Female | 220 | 55.3% |
| Nonbinary | 24 | 6.0% |
| Education | | |
| Some High School or Lower | 1 | 0.3% |
| High School / GED | 252 | 63.3% |
| Associate Degree | 66 | 16.6% |
| Bachelor’s Degree | 69 | 17.3% |
| Master’s Degree | 9 | 2.3% |
| Doctorate Degree | 1 | 0.3% |
| Race | | |
| White/Caucasian | 217 | 54.55 |
| Black/African American | 64 | 16.1% |
| Asian | 105 | 26.4% |
| American Indian or Alaska Native | 9 | 2.3% |
| Native Hawaiian or Other Pacific Islander | 3 | 0.8% |

Total Statistics and Cronbach's Alpha

Table 4 presents reliability and validity results for various constructs related to students' attitudes and behaviors toward AI. The mean scores vary significantly across constructs, reflecting different levels of agreement. For instance, students' attitudes toward AI (ATT) show a broad range, with some items scoring above 5, such as ATT1 (6.02), while others fall below 4, like ATT3 (3.89). Similarly, the actual use of AI (SU) tends to have lower mean scores, with SU1 at 2.31, indicating weaker engagement with AI tools. The variability in responses is also evident in standard deviation and variance measures, where items like SU10 exhibit exceptionally high variance (4.262), signaling substantial dispersion in responses. In contrast, PB1 (5.49, SD = 1.238) shows more consistency, suggesting that students feel relatively stable in their perceived behavioral control toward AI.

Reliability coefficients, measured through Cronbach's Alpha, indicate strong internal consistency for most constructs. AI anxiety (SA) has the highest reliability (0.881), suggesting that the items measuring students' anxiety toward AI are consistent and reliable. Other constructs, such as perceived behavioral control (PB, 0.731) and subjective norms (SN, 0.722), also demonstrate acceptable reliability levels, while students' attitudes (ATT, 0.763) and behavioral intention toward AI (SI, 0.758) indicate relatively strong internal consistency. However, SU and SN exhibit higher item variances, suggesting greater dispersion in responses. This variability may indicate inconsistencies in how students perceive social influences and their actual use of AI.

Certain items, particularly in SN and SU, have notably low mean scores and high variability, raising potential concerns about their measurement effectiveness. For example, SN3 (2.96, SD = 1.787, Var = 3.195) and SU1 (2.31, SD = 1.836, Var = 3.372) suggest weaker alignment with the construct indicating varying student perceptions. Overall, AI anxiety (SA) is the most reliable construct, while the actual use of AI (SU) exhibits the greatest variability and lowest mean scores. Students' attitudes (ATT) and perceived behavioral control (PB) display relatively stable response patterns, indicating stronger and more consistent measurement.

**Table 4 - Reliability and Validity**

| Variable | Items | Mean | Standard Deviation | Variance | CA |
|---|---|---|---|---|---|
| ATT | ATT1 | 6.02 | 1.049 | 1.1 | 0.763 |
| | ATT2 | 4.09 | 1.835 | 3.368 | |
| | ATT3 | 3.89 | 1.844 | 3.401 | |
| | ATT4 | 4.09 | 1.796 | 3.227 | |
| | ATT5 | 5.29 | 1.339 | 1.793 | |
| | ATT6 | 3.71 | 1.516 | 2.299 | |
| | ATT7 | 4.99 | 1.605 | 2.577 | |
| | ATT8 | 5.05 | 1.576 | 2.484 | |
| | ATT9 | 3.56 | 1.887 | 3.562 | |
| | ATT10 | 4.77 | 1.779 | 3.166 | |
| | ATT11 | 4.57 | 1.76 | 3.097 | |
| | ATT12 | 4.99 | 1.593 | 2.539 | |
| | ATT14 | 4.39 | 1.701 | 2.894 | |
| | ATT14 | 4.31 | 1.694 | 2.87 | |
| | ATT15 | 3.68 | 2.038 | 4.153 | |
| SN | SN1 | 5.23 | 1.344 | 1.807 | 0.722 |
| | SN2 | 3.14 | 1.693 | 2.865 | |
| | SN3 | 2.96 | 1.787 | 3.195 | |
| | SN4 | 2.98 | 1.855 | 3.44 | |
| | SN5 | 3.25 | 2.211 | 4.888 | |
| | SN7 | 5.58 | 1.435 | 2.059 | |
| | SN8 | 4.79 | 2.099 | 4.407 | |
| | SN10 | 4.1 | 1.315 | 1.729 | |
| PB | PB1 | 5.49 | 1.238 | 1.533 | 0.731 |
| | PB2 | 3.2 | 1.497 | 2.242 | |
| | PB3 | 4.84 | 1.722 | 2.964 | |
| | PB4 | 4.75 | 1.606 | 2.578 | |
| | PB5 | 4.27 | 1.688 | 2.85 | |

| | | | | | |
|---|---|---|---|---|---|
| | PB6 | 4.89 | 1.68 | 2.822 | |
| | PB7 | 3.99 | 1.89 | 3.572 | |
| | PB8 | 4.86 | 1.523 | 2.321 | |
| | PB9 | 5.13 | 1.482 | 2.196 | |
| | PB10 | 2.74 | 1.788 | 3.197 | |
| SA | SA1 | 3.54 | 1.845 | 3.403 | 0.881 |
| | SA2 | 3.34 | 1.761 | 3.103 | |
| | SA3 | 4.93 | 1.69 | 2.856 | |
| | SA4 | 4.42 | 1.88 | 3.534 | |
| | SA5 | 3.71 | 1.882 | 3.542 | |
| | SA6 | 3.13 | 1.661 | 2.759 | |
| | SA7 | 2.98 | 1.68 | 2.821 | |
| | SA8 | 4.39 | 1.853 | 3.432 | |
| | SA9 | 5.4 | 1.527 | 2.331 | |
| | SA10 | 5.42 | 1.583 | 2.507 | |
| | SA11 | 3.61 | 1.707 | 2.915 | |
| | SA12 | 4.04 | 1.751 | 3.067 | |
| | SA13 | 4.07 | 1.814 | 3.292 | |
| | SA14 | 5.81 | 1.426 | 2.032 | |
| | SA15 | 3.27 | 1.799 | 3.235 | |
| | SA16 | 5.34 | 1.738 | 3.02 | |
| | SA17 | 5.63 | 1.386 | 1.921 | |
| | SA18 | 5.59 | 1.576 | 2.484 | |
| | SA19 | 5.11 | 1.76 | 3.096 | |
| | SA20 | 4.92 | 1.885 | 3.552 | |
| | SA21 | 4.79 | 1.92 | 3.685 | |
| SI | SI1 | 4.12 | 2.013 | 4.054 | 0.758 |
| | SI2 | 3.48 | 1.873 | 3.51 | |
| | SI4 | 4.09 | 1.9 | 3.61 | |
| | SI3 | 3.9 | 1.689 | 2.851 | |
| | SI5 | 4.24 | 1.751 | 3.066 | |
| SU | SU1 | 2.31 | 1.836 | 3.372 | 0.798 |
| | SU2 | 2.91 | 2.194 | 4.813 | |
| | SU3 | 3.63 | 2.007 | 4.038 | |
| | SU4 | 3.88 | 2.021 | 4.084 | |
| | SU5 | 3.60 | 1.852 | 3.429 | |
| | SU6 | 2.81 | 1.848 | 3.414 | |
| | SU7 | 3.49 | 2.121 | 4.497 | |
| | SU8 | 4.34 | 2.185 | 4.773 | |
| | SU9 | 4.46 | 1.961 | 3.846 | |
| | SU10 | 3.67 | 3.064 | 4.262 | |
| | SU11 | 2.26 | 1.640 | 2.688 | |
| | SU12 | 3.57 | 1.706 | 2.911 | |
| | SU13 | 2.38 | 1.590 | 2.528 | |

## Descriptive Statistics and Tests of Normality

According to Table 5, Students generally have a positive attitude toward AI ($\bar{x}$ = 4.5676, s = 0.9317), which is the highest mean among all variables. This suggests that overall, students view AI favorably. Similarly, PB ($\bar{x}$ = 4.4166, s = 0.8750) and SN ($\bar{x}$ = 4.0025, s = 1.0174) indicate a moderate level of agreement, suggesting that students believe they have an element of control over their use of AI and that their peers influence these attitudes.

SA ($\bar{x}$ = 4.4496, s = 0.9387) is also relatively high, indicating that despite positive attitudes, many students experience some level of apprehension toward AI. SI ($\bar{x}$ = 3.9664, s = 1.1379) is slightly lower than ATT and PB, which might indicate that while students have a positive outlook, they are somewhat hesitant to fully commit to using AI.

The skewness and kurtosis values indicate that the data distribution is fairly normal, though some variables, such as SN and SU, exhibit mild positive skewness, indicating that more students report lower-than-average values for these constructs. The kurtosis values are mostly close to zero, revealing a normal distribution. SU has a slight negative kurtosis, meaning a flatter distribution with more spread-out responses.

**Table 5 - Variable Descriptive Statistics**

| | N | Mean | Std. Deviation | Skewness Statistic | Skewness Std. Error | Kurtosis Statistic | Kurtosis Std. Error |
|---|---|---|---|---|---|---|---|
| ATT_avg | 398 | 4.5676 | 0.93168 | -0.533 | 0.122 | -0.128 | 0.244 |
| SN_avg | 398 | 4.0025 | 1.01740 | 0.93 | 0.122 | -0.188 | 0.244 |
| PB_avg | 398 | 4.4166 | 0.87501 | -0.281 | 0.122 | -0.035 | 0.244 |
| SA_avg | 398 | 4.4496 | 0.93877 | -0.468 | 0.122 | 0.289 | 0.244 |
| SI_avg | 398 | 3.9664 | 1.31795 | -0.346 | 0.122 | -0.550 | 0.244 |
| SU_avg | 398 | 3.3311 | 1.02346 | 0.193 | 0.122 | -0.791 | 0.244 |

Table 6 presents results from normality tests using both the Kolmogorov-Smirnov and Shapiro-Wilk tests. For both tests, the significance values indicate whether the data deviates from a normal distribution. A significance value below 0.05 suggests a violation of normality. The Kolmogorov-Smirnov test shows that all variables have a significance value of less than 0.05, except for SN ($p = 0.020$), indicating that most variables do not follow a normal distribution. The Shapiro-Wilk test provides a more stringent check for normality, and here, SN is the only variable that fails to show a significant deviation ($p = 0.165$). All other variables exhibit significance values below 0.05, further confirming that their distributions deviate from normality. SA, SI, and SU show the strongest deviation from normality, as indicated by their particularly low significance values in both tests ($p < 0.001$). In contrast, SN appears to be the closest to a normal distribution, as suggested by both tests.

**Table 6 - Tests of Normality**

| | Kolmogorov-Smirnova | | | Shapiro-Wilk | | |
|---|---|---|---|---|---|---|
| | Statistic | df | Sig. | Statistic | df | Sig. |
| ATT_avg | 0.072 | 398 | <.001 | 0.975 | 398 | <.001 |
| SN_avg | 0.050 | 398 | 0.020 | 0.994 | 398 | 0.165 |
| PB_avg | 0.062 | 398 | <.001 | 0.991 | 398 | 0.020 |
| SA_avg | 0.055 | 398 | 0.006 | 0.985 | 398 | <.001 |
| SI_avg | 0.090 | 398 | <.001 | 0.973 | 398 | <.001 |
| SU_avg | 0.072 | 398 | <.001 | 0.979 | 398 | <.001 |

**Construct Validity and Correlation Analysis**

The correlation matrix in Table 7 provides insights into the relationships between each variable, displaying several significant correlations emerging from the data. First, gender exhibits notable correlations with multiple AI-related variables. It is negatively correlated with ATT (-.217), SN (-.155), PB (-.349), SI (-.269), and SU(-.295), all at significant levels ($p < 0.01$). This suggests that males and females differ in their perceptions and behaviors toward AI, with females potentially showing lower attitudes, perceived social support, and behavioral control regarding AI use.

SA is another key factor that displays negative correlations with ATT (-.195), SN (-.262), PB (-.262), SI (-.240), and SU (-.265), all significant at $p < 0.01$. This suggests that students with higher AI anxiety tend to have lower attitudes, lower social acceptance, and lower perceived behavioral control, which in turn may reduce their AI adoption.

PB has strong positive correlations with ATT (.550), SN (.569), SI (.600), and SU(.554), all significant at $p < 0.01$. This implies that students who feel more in control of using AI are more likely to have positive attitudes, experience stronger social influences, and ultimately use AI more frequently.

SI and SN are strongly correlated with actual AI use (.794 and .510; $p < 0.01$). This highlights that students who perceive AI as socially encouraged are significantly more likely to engage in actual AI use.

Finally, ATT and SU exhibit a strong correlation (.740, $p < 0.01$), indicating that students with positive attitudes toward AI are far more likely to incorporate AI into their behaviors. Based on these results, behavioral control, social influence, and attitudes toward AI were all shown to play significant roles in the adoption of AI among students.

## Table 7 - Variable Correlations

| | | Age | Gender | Education | Race | ATT_avg | SN_avg | PB_avg | SA_avg | SI_avg | SU_avg |
|---|---|---|---|---|---|---|---|---|---|---|---|
| Age | Pearson | 1 | 0.036 | .159** | -0.013 | 0.041 | 0.014 | 0.022 | -.117* | 0.093 | 0.069 |
| | Sig (2-tail) | | 0.473 | 0.001 | 0.797 | 0.419 | 0.774 | 0.656 | 0.019 | 0.063 | 0.168 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| Gender | Pearson | 0.036 | 1 | 0.017 | -.125* | -.217** | -.155** | -.349** | .182** | -.269** | -.295** |
| | Sig (2-tail) | 0.473 | | 0.736 | 0.013 | <.001 | 0.002 | <.001 | <.001 | <.001 | <.001 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| Education | Pearson | .159** | 0.017 | 1 | 0.021 | 0.054 | 0.002 | 0.015 | 0.034 | 0.047 | 0.033 |
| | Sig (2-tail) | 0.001 | 0.736 | | 0.677 | 0.284 | 0.965 | 0.763 | 0.495 | 0.345 | 0.515 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| Race | Pearson | -0.013 | -.125* | 0.021 | 1 | 0.079 | 0.071 | .119* | -0.074 | 0.095 | 0.087 |
| | Sig (2-tail) | 0.797 | 0.013 | 0.677 | | 0.117 | 0.159 | 0.018 | 0.142 | 0.06 | 0.082 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| ATT_avg | Pearson | 0.041 | -.217** | 0.054 | 0.079 | 1 | .550** | .569** | -.195** | .794** | .740** |
| | Sig (2-tail) | 0.419 | <.001 | 0.284 | 0.117 | | <.001 | <.001 | <.001 | <.001 | <.001 |
| | N | 397 | 397 | 397 | 397 | 397 | 397 | 397 | 397 | 397 | 397 |
| SN_avg | Pearson | 0.014 | -.155** | 0.002 | 0.071 | .550** | 1 | .512** | -0.011 | .584** | .510** |
| | Sig (2-tail) | 0.774 | 0.002 | 0.965 | 0.159 | <.001 | | <.001 | 0.829 | <.001 | <.001 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| PB_avg | Pearson | 0.022 | -.349** | 0.015 | .119* | .569** | .512** | 1 | -.262** | .600** | .554** |
| | Sig (2-tail) | 0.656 | <.001 | 0.763 | 0.018 | <.001 | <.001 | | <.001 | <.001 | <.001 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| SA_avg | Pearson | -.117* | .182** | 0.034 | -0.074 | -.195** | -0.011 | -.262** | 1 | -.240** | -.265** |
| | Sig (2-tail) | 0.019 | <.001 | 0.495 | 0.142 | <.001 | 0.829 | <.001 | | <.001 | <.001 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| SI_avg | Pearson | 0.093 | -.269** | 0.047 | 0.095 | .794** | .584** | .600** | -.240** | 1 | .794** |
| | Sig (2-tail) | 0.063 | <.001 | 0.345 | 0.06 | <.001 | <.001 | <.001 | <.001 | | <.001 |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |
| SU_avg | Pearson | 0.069 | -.295** | 0.033 | 0.087 | .740** | .510** | .554** | -.265** | .794** | 1 |
| | Sig (2-tail) | 0.168 | <.001 | 0.515 | 0.082 | <.001 | <.001 | <.001 | <.001 | <.001 | |
| | N | 398 | 398 | 398 | 398 | 397 | 398 | 398 | 398 | 398 | 398 |

* Correlation is significant at the 0.05 level (2-tailed).

** Correlation is significant at the 0.01 level (2-tailed).

**Regression Analysis Results**

Table 8 presents results indicating that ATT has a significant positive impact on behavioral intention (SI) ($\beta = 0.767$, $t = 24.754$, $p < .001$) controlling for age, gender, and education level. This suggests that for every unit increase in ATT, SI increases by 0.767 units, reinforcing the model's predicted relationship. The results confirm H1, highlighting that students who hold more favorable attitudes toward AI are substantially more inclined to use it.

Findings for H2 reveal that SN significantly predicts SI ($\beta = 0.552$, $t = 13.743$, $p < .001$) controlling for age, gender, and education level. This finding suggests that students who perceive higher social encouragement and normative pressure toward AI adoption are far more likely to intend to use it. The strong positive relationship validates H2, underlining the importance of social influence in technology acceptance.

Support for H3 was revealed as PB was found to be a strong determinant of SI ($\beta = 0.571$, $t = 13.313$, $p < .001$) controlling for age, gender, and education level. This suggests that as students' confidence in their ability to use AI grows, so does their intention to integrate it into their academic or professional routines.

Findings further demonstrate that PB is also a key factor influencing actual AI use (SU) ($\beta = 0.51$, $t = 11.453$, $p < .001$) controlling for age, gender, and education level. This strong positive association confirms H4, suggesting that students who feel capable of using AI are significantly more likely to actively engage with it.

**Table 8 - Summary Results for Hypotheses**

| Hypothesis 1 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | -3.306 | 0.001 |
| Age | 0.066 | 2.171 | 0.031 |
| Gender | -0.102 | -3.28 | 0.001 |
| Education | -0.003 | -0.083 | 0.934 |
| Race | 0.023 | 0.758 | 0.449 |
| ATT_avg | 0.767 | 24.754 | <.001 |

a. Dependent Variable: SI_avg

| Hypothesis 2 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | 2.36 | 0.019 |
| Age | 0.087 | 2.16 | 0.031 |
| Gender | -0.183 | -4.526 | <.001 |
| Education | 0.035 | 0.867 | 0.386 |
| Race | 0.033 | 0.827 | 0.409 |
| SN_avg | 0.552 | 13.743 | <.001 |

b. Dependent Variable: SI_avg

| Hypothesis 3 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | -0.553 | 0.58 |
| Age | 0.079 | 1.945 | 0.053 |
| Gender | -0.07 | -1.635 | 0.103 |
| Education | 0.027 | 0.666 | 0.506 |
| Race | 0.018 | 0.456 | 0.648 |
| PB_avg | 0.571 | 13.313 | <.001 |

a. Dependent Variable: SI_avg

| Hypothesis 4 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | 1.68 | 0.094 |

| | | | |
|---|---|---|---|
| Age | 0.06 | 1.413 | 0.158 |
| Gender | -0.118 | -2.647 | 0.008 |
| Education | 0.017 | 0.409 | 0.683 |
| Race | 0.012 | 0.296 | 0.767 |
| PB_avg | 0.51 | 11.453 | <.001 |

a. Dependent Variable: SU_avg

Table 9 shows the results of the mediating variables in the model controlling for age, gender, and education level. They indicate that SI mediates the relationship between ATT and SU. The standard coefficient for SI_avg is $\beta = 0.77$, $t = 24.215$, $p < .001$, demonstrating a strong and statistically significant positive impact on actual AI use. This suggests that students with more positive attitudes toward AI are more likely to develop an intention to use AI, which in turn leads to actual AI adoption. H5 is supported, reinforcing that behavioral intention acts as a mediating factor in the relationship between attitudes and AI usage.

The analysis also reveals that SI partially mediates the relationship between ATT and SU. In Model 1, ATT directly predicts SU ($\beta = 0.706$, $t = 20.681$, $p < .001$). However, when SI is introduced in Model 2, ATTs effect decreases ($\beta = 0.296$, $t = 6.182$, $p < .001$), while SI remains strongly significant ($\beta = 0.534$, $t = 10.955$, $p < .001$). This reduction in ATT's direct effect suggests that SI plays a substantial role in explaining the relationship between attitudes toward AI and actual AI use. H6 is supported, confirming that behavioral intention serves as a key mechanism through which positive attitudes lead to actual AI adoption.

The results of H7 suggest that SI fully mediates the relationship between SN and SU. In Model 1, SN significantly predicts SU ($\beta = 0.473$, $t = 11.147$, $p < .001$), indicating that social influence initially plays a strong role in AI use. However, in Model 2, SN becomes non-significant ($\beta = 0.07$, $t = 1.877$, $p = 0.061$), while SI strongly predicts SU ($\beta = 0.729$, $t = 18.885$, $p < .001$). This suggests that subjective norms influence actual AI use only indirectly through behavioral intention, meaning that social pressure alone does not directly translate into AI use; it must first shape students' intention to adopt AI. H7 is supported with a partial mediation, reinforcing the role of behavioral intention in social influence on AI adoption.

The findings for H8 also reveal partial mediation of SI in the relationship between PB and SU. In Model 1, PB significantly predicts SU ($\beta = 0.51$, $t = 11.453$, $p < .001$). However, after introducing SI, the effect of PB decreases ($\beta = 0.102$, $t = 2.611$, $p = 0.009$), while SI remains a strong predictor of SU ($\beta = 0.715$, $t = 18.786$, $p < .001$). This indicates that PB influences actual AI use both directly and indirectly through behavioral intention, meaning that students who feel confident in using AI are more likely to form an intention to use it, which subsequently leads to actual AI adoption. H8 is therefore supported.

**Table 9 - Summary Results for Hypotheses (Mediation)**

| Hypothesis 5 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | 5.241 | <.001 |
| Age | 0.001 | 0.035 | 0.972 |
| Gender | -0.088 | -2.763 | 0.006 |
| Education | -0.003 | -0.085 | 0.933 |
| Race | 0.004 | 0.115 | 0.908 |
| SI_avg | 0.77 | 24.215 | <.001 |

a. Dependent Variable: SU_avg

| Hypothesis 6 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | -0.183 | 0.855 |
| Age | 0.047 | 1.405 | 0.161 |
| Gender | -0.142 | -4.151 | <.001 |
| Education | -0.01 | -0.291 | 0.771 |
| Race | 0.016 | 0.474 | 0.636 |
| ATT_avg | 0.706 | 20.681 | <.001 |
| 2 (Constant) | | 1.6 | 0.11 |
| Age | 0.012 | 0.4 | 0.689 |
| Gender | -0.088 | -2.884 | 0.004 |
| Education | -0.008 | -0.286 | 0.775 |
| Race | 0.004 | 0.121 | 0.904 |
| ATT_avg | 0.296 | 6.182 | <.001 |
| SI_avg | 0.534 | 10.955 | <.001 |

a. Dependent Variable: SU_avg

| Hypothesis 7 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | 4.697 | <.001 |
| Age | 0.067 | 1.579 | 0.115 |
| Gender | -0.222 | -5.196 | <.001 |
| Education | 0.024 | 0.571 | 0.568 |
| Race | 0.027 | 0.629 | 0.53 |

| | | | |
|---|---|---|---|
| SN_avg | 0.473 | 11.147 | <.001 |
| 2 (Constant) | | 4.206 | <.001 |
| Age | 0.004 | 0.12 | 0.905 |
| Gender | -0.088 | -2.787 | 0.006 |
| Education | -0.001 | -0.039 | 0.969 |
| Race | 0.002 | 0.079 | 0.937 |
| SN_avg | 0.07 | 1.877 | 0.061 |
| SI_avg | 0.729 | 18.885 | <.001 |

a. Dependent Variable: SU_avg

| Hypothesis 8 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | 1.68 | 0.094 |
| Age | 0.06 | 1.413 | 0.158 |
| Gender | -0.118 | -2.647 | 0.008 |
| Education | 0.017 | 0.409 | 0.683 |
| Race | 0.012 | 0.296 | 0.767 |
| PB_avg | 0.51 | 11.453 | <.001 |
| 2 (Constant) | | 2.838 | 0.005 |
| Age | 0.003 | 0.101 | 0.919 |
| Gender | -0.068 | -2.088 | 0.037 |
| Education | -0.002 | -0.068 | 0.946 |
| Race | -0.001 | -0.025 | 0.98 |
| PB_avg | 0.102 | 2.611 | 0.009 |
| SI_avg | 0.715 | 18.786 | <.001 |

a. Dependent Variable: SU_avg

H9, H10 and H11 pertained to the moderation variables controlling for age, gender, and education. The results are shown in Table 10. Surprisingly, none of them were supported. The numbers for H7 suggest that AI anxiety (SA) does not significantly moderate the relationship between ATT and SI ($\beta = -0.054$, $t = -1.61$, $p = 0.108$). This means that AI anxiety does not significantly alter the effect of attitudes on AI use.

However, the direct effects of ATT_mc ($\beta = 0.69$, $t = 20.215$, $p < .001$) and SA_mc ($\beta = -0.093$, $t = -2.703$, $p = 0.007$) remain significant. H9 is therefore not supported, as it does not moderate the strength of the attitude-AI use relationship.

For H10, the findings reveal that SA does not moderate the relationship between SN and SI ($\beta = -0.021$, $t = -0.514$, $p = 0.608$. The direct relationships remain strong, with SN_mc ($\beta = 0.475$, $t = 11.349$, $p < .001$) and SA_mc ($\beta = -0.22$, $t = -5.268$, $p < .001$) still showing significant effects. As a result, H10 is also not supported, indicating that although AI anxiety directly influences AI use, it does not change the strength of the relationship between social influence and intention.

The results of H11 indicate that SA does not significantly moderate the relationship between PB and SI. PB_SA does not reach significance ($\beta = -0.036$, $t = -0.846$, $p = 0.398$), suggesting that AI anxiety does not alter the effect of perceived behavioral control on AI use. However, both PB_mc ($\beta = 0.482$, $t = 10.637$, $p < .001$) and SA_mc ($\beta = -0.105$, $t = -2.267$, $p = 0.018$) remain significant, demonstrating that perceived behavioral control continues to play a crucial role in intention to adopt AI, while AI anxiety independently hinders it. As a result, H11 is not supported.

**Table 10 - Summary Results for Hypotheses (Moderation)**

| Hypothesis 9 | | | |
|---|---|---|---|
| Model | Beta | t | Sig. |
| 1 (Constant) | | 15.541 | <.001 |
| Age | 0.035 | 1.031 | 0.303 |
| Gender | -0.127 | -3.722 | <.001 |
| Education | -0.004 | -0.113 | 0.91 |
| Race | 0.011 | 0.334 | 0.739 |
| ATT_mc | 0.691 | 20.199 | <.001 |
| SA_mc | -0.101 | -2.949 | 0.003 |
| 2 (Constant) | | 15.65 | <.001 |
| Age | 0.029 | 0.857 | 0.392 |
| Gender | -0.134 | -3.901 | <.001 |
| Education | 0.001 | 0.027 | 0.979 |
| Race | 0.011 | 0.322 | 0.748 |
| ATT_mc | 0.69 | 20.215 | <.001 |
| SA_mc | -0.093 | -2.703 | 0.007 |
| ATT_SA | -0.054 | -1.61 | 0.108 |

a. Dependent Variable: SI_avg

| Hypothesis 10 | | | |
| --- | --- | --- | --- |
| Model | Beta | t | Sig. |
| 1 (Constant) | | 12.674 | <.001 |
| Age | 0.037 | 0.902 | 0.368 |
| Gender | -0.181 | -4.319 | <.001 |
| Education | 0.036 | 0.88 | 0.379 |
| Race | 0.014 | 0.348 | 0.728 |
| SN_mc | 0.478 | 11.655 | <.001 |
| SA_mc | -0.222 | -5.349 | <.001 |
| 2 (Constant) | | 12.61 | <.001 |
| Age | 0.034 | 0.813 | 0.416 |
| Gender | -0.182 | -4.339 | <.001 |
| Education | 0.038 | 0.912 | 0.362 |
| Race | 0.013 | 0.309 | 0.758 |
| SN_mc | 0.475 | 11.49 | <.001 |
| SA_mc | -0.22 | -5.268 | <.001 |
| SN_SA | -0.021 | -0.514 | 0.608 |

a. Dependent Variable: SI_avg

| Hypothesis 11 | | | |
| --- | --- | --- | --- |
| Model | Beta | t | Sig. |
| 1 (Constant) | | 11.614 | <.001 |
| Age | 0.045 | 1.074 | 0.283 |
| Gender | -0.106 | -2.386 | 0.017 |
| Education | 0.024 | 0.565 | 0.573 |
| Race | 0.008 | 0.196 | 0.845 |
| PB_mc | 0.485 | 10.733 | <.001 |
| SA_mc | -0.113 | -2.612 | 0.009 |
| 2 (Constant) | | 11.622 | <.001 |
| Age | 0.044 | 1.04 | 0.299 |
| Gender | -0.109 | -2.436 | 0.015 |
| Education | 0.025 | 0.586 | 0.558 |
| Race | 0.008 | 0.187 | 0.852 |
| PB_mc | 0.482 | 10.637 | <.001 |
| SA_mc | -0.105 | -2.367 | 0.018 |
| PB_SA | -0.036 | -0.846 | 0.398 |

a. Dependent Variable: SI_avg

The Sobel test was employed to evaluate the mediating effect of behavioral intention and the actual use of AI tools by college students on each of the independent variables. Three values are obtained from the Sobel test: the test statistic, standard error, and p-value. Table 11 provides a summary, using SI as the mediating variable between ATT and SU, SN and SU, and PB and SU. The results show that all p-values are below the alpha value of 0.05, indicating that the mediation effects are statistically significant. This confirms that behavioral intention significantly mediates the relationship between the TPB constructs and students' actual use of AI tools in academic settings.

**Sobel Tests**

**Table 11 - Sobel Test for Mediators**

| Hypothesis 6 | | | | | |
|---|---|---|---|---|---|
| | Input | | Test Statistic | Std. Error | p-value |
| a | 1.124 | Sobel Test: | 18.3291 | 0.0378 | 0.0000 |
| b | 0.617 | Aroian Test: | 18.3223 | 0.0379 | 0.0000 |
| SEa | 0.043 | Goodman Test: | 18.3359 | 0.3782 | 0.0000 |
| SEb | 0.024 | | | | |

| Hypothesis 7 | | | | | |
|---|---|---|---|---|---|
| | Input | | Test Statistic | Std. Error | p-value |
| a | 0.757 | Sobel Test: | 12.4855 | 0.0374 | 0.0000 |
| b | 0.617 | Aroian Test: | 12.4783 | 0.0374 | 0.0000 |
| SEa | 0.053 | Goodman Test: | 12.4927 | 0.0274 | 0.0000 |
| SEb | 0.024 | | | | |

| Hypothesis 8 | | | | | |
|---|---|---|---|---|---|
| | Input | | Test Statistic | Std. Error | p-value |
| a | 0.904 | Sobel Test: | 12.8392 | 0.4344 | 0.0000 |
| b | 0.617 | Aroian Test: | 12.8319 | 0.0435 | 0.0000 |
| SEa | 0.061 | Goodman Test: | 12.8465 | 0.0434 | 0.0000 |
| SEb | 0.024 | | | | |

**Summary of Results**

**Table 12 - Hypotheses Results**

| | **Hypotheses Results** | **Supported?** |
|---|---|---|
| H1+ | As students' attitudes towards AI (ATT) become positive, their behavioral intention towards the use of AI (SI) will increase. | Yes |
| H2+ | As students' subjective norms (SN) towards AI become positive, their behavioral intention towards the use of AI (SI) will increase. | Yes |
| H3+ | As students' perceived behavioral control (PB) towards AI become positive, their behavioral intention towards the use of AI (SI) will increase. | Yes |
| H4+ | As students' perceived behavioral control towards AI (PB) become positive, their actual use of AI (SU) will increase. | Yes |
| H5+ | As students' behavioral intent towards AI (SI) becomes positive, their actual use of AI (SU) will increase. | Yes |
| H6+ | A students' behavioral intent (SI) mediates the relationship between Students Attitude (AT) and actual use of AI (SU) in school | Yes |
| H7+ | A students' behavioral intent (SI) mediates the relationship between subjective norms (SN) and actual use of AI (SU) in school. | Yes |
| H8+ | A students' perceived behavioral control towards AI (PB) mediates the relationship between subjective norms (SN) and actual use of AI (SU) in school. | Yes |
| H9- | A college student's AI anxiety (SA) will moderate the relationship between attitude (ATT) and intent to use AI in school (SI), such that as anxiety increases, the relationship between attitude and intent weakens. | No |
| H10- | A college student's AI anxiety (SA) will moderate the relationship between subjective norms (SN) and intent to use AI in school (SI), such that as anxiety increases, the relationship between subjective norms and intent weakens. | No |
| H11- | A college student's AI anxiety (SA) will moderate the relationship between perceived behavioral control (PB) and intent (SI), such that as anxiety increases, the relationship between perceived behavioral control and intent weakens. | No |

# CHAPTER V – DISCUSSION

## Summary of Findings

This study brought to light insights that further validate Azjen's 1991 Theory of Planned Behavior. Students' intentions and actual use of AI technologies were shown to be significantly influenced by how they feel about AI, the social pressure they perceive, and the degree of control they believe they have (Roetzer, 2022). Attitudes stood out in particular, as a more favorable view of AI corresponded with a significantly higher intention to use it. Social influence also played a significant role; the more students felt that important people in their lives supported AI use, the more likely they were to intend to use it (Strzelecki, 2024).

Perceived behavioral control played a key role in shaping both students' intentions and their actual use of AI. Students who believed they had the ability to use AI were significantly more likely to intend to use it and to follow through in practice (Pedro et al., 2019). Simply put, the stronger their sense of control, the more likely they were to engage with AI tools.

Behavioral intention proved to be a strong predictor of actual AI use, making it clear that intention plays a central role in the adoption of AI. It also functions as a partial mediator between attitude and behavior: while attitude directly impacts AI use, a meaningful portion of that influence is carried through intention.

The findings show that behavioral intention serves as a key link in the relationship between subjective norms and actual AI use (Lim et al., 2023). Once intention is added to the model, the beta drops, indicating full mediation. It also partially explains the effect of perceived behavioral control on AI use.

While the moderating effects of AI anxiety were not statistically significant, its theoretical integration reveals the importance of accounting for affective-emotional dimensions in behavioral models, particularly in settings characterized by technological change and uncertainty (Li & Huang, 2020). The findings make it clear that intention plays a central role in whether students actually go on to use AI tools. It acts as the key link between what they believe and how they behave, helping translate perceptions into action (Kim et al., 2020). Encouraging positive attitudes, building a supportive social environment, and helping students feel more confident in their ability to use AI are all key to successfully integrating these tools into education (Lo, 2023).

**Theoretical Implications**

This research advances the theoretical understanding in the domains of technology adoption and behavioral psychology by extending the TPB to the context of generative AI adoption in higher education (Firat, 2023). The results reaffirm the predictive validity of the TPB's core constructs - attitude, subjective norms, and perceived behavioral control - in shaping both behavioral intention and actual usage of AI tools among college students (Ajzen, 2025). The robust significance of these constructs align with and support prior literature on technology acceptance, thereby reinforcing the TPB as a suitable and enduring framework for analyzing user behavior in emerging technological contexts (Alzahrani, 2023).

The inclusion of AI anxiety as a moderating variable represents a novel contribution to the TPB literature (Bender, 2023). While the moderating effects of AI anxiety were not statistically significant, its theoretical integration reveals the importance of accounting for affective-emotional dimensions in behavioral models, particularly in settings characterized by technological change and uncertainty (Celik, 2023). This finding suggests that, although students may report elevated levels of anxiety regarding AI, such affective responses do not substantially alter the relationships between the TPB constructs and behavioral intention. This outcome invites further theoretical exploration into the boundaries of TPB when applied to emotionally charged or ethically complex technologies.

Furthermore, the study provides empirical support for the mediating role of behavioral intention in the relationships between attitude, subjective norms, perceived behavioral control, and actual AI use (Ajzen, 2020). This finding substantiates Ajzen's (1991) original proposition that intention serves as the most proximal antecedent to behavior, particularly in contexts requiring volitional engagement with novel tools. The mediation results also highlight the sequential nature of decision-making processes, wherein cognitive evaluations (attitudes, norms, and control perceptions) crystallize into intention, which in turn drives observable behavior (Ajzen, 2015).

By situating generative AI within the TPB framework, this research expands the theoretical utility of the model to accommodate the complexities of AI-enhanced educational environments (Adetayo, 2024). It also identifies the potential for future model extensions that integrate psychological constructs, such as anxiety, self-efficacy, or perceived ethical risk. Such extensions may yield richer, more nuanced accounts of user behavior, particularly as AI technologies continue to evolve in sophistication and prevalence.

### Study Limitations

There are a few important limitations to consider when interpreting these results. The sample was largely made up of young adults in educational settings, which means the findings may not fully apply to older learners, working professionals, or individuals outside the academic world (Roetzer, 2022). These groups may engage with AI in different ways, facing a range of challenges and levels of familiarity that weren't captured in this study. They were each willing to fill out a 10-minute survey for USD $3.00 total, which suggests they are willing to work for relatively little money. This probably influenced the socio-economic status of the individuals willing to participate in the collection of both quantitative and qualitative data sets.

Another limitation lies in the cross-sectional design of the study, which captures just a snapshot in time (Peart et al., 2022). This makes it difficult to draw conclusions about cause and effect or to observe how students' perceptions and behaviors toward AI evolve. Given how quickly AI is advancing and becoming part of everyday life, future research using longitudinal methods would offer a better view of how attitudes and usage patterns shift over time (Ajzen, 2015).

The potential for response bias is yet another important limitation. Some participants may have answered in ways they thought were more socially acceptable, rather than sharing their genuine thoughts. There's also the chance that some misunderstood the survey questions either because of how they were worded or due to the technical nature of the topicwhich could lead to responses that don't fully reflect their actual experiences or opinions about AI.

The study also found a high degree of variability in responses related to Subjective Norms and Actual Use, pointing to notable differences in how participants experience social pressure and interact with AI tools. This inconsistency suggests that other influential factors—possibly not accounted for in the current model—may be shaping these behaviors (Wang & Wang, 2022). As a result, the precision and reliability of the findings may be affected. Future research may benefit from using more refined and targeted measures to better capture the complex realities surrounding AI adoption (Tufekci, 2013).

**Suggestions for Future Research**

As AI continues to weave itself into everyday life, understanding its broader societal impact becomes more important than ever (Peart et al., 2022). In addition to the 400 students who answered with the numerical survey responses, the same research study populated an additional quantitative data set worth exploring. For example,

1) 398 students answered the following questions in one phrase or sentence:
    a. What's one thing about AI that makes you anxious?
    b. What's one thing about AI that empowers you?
2) 22 undergraduate student case studies from a "Data Visualization" course:
    a. Written by students on Medium.com as opinion pieces

b. Focused on interactive visualizations
c. Students answer the following seven questions (below)
d. Graded for accuracy and effort

The first data set mentioned includes responses from 398 individuals who completed both the Likert-scale survey questions and two open-ended questions. Participants shared what aspects of AI made them anxious and which features they find empowering. The responses offer a window into the emotional landscape surrounding AI, revealing a wide range of concerns and perceived advantages that appear to differ by demographic and psychographic profiles.

The second qualitative data set comes from a group of 22 students at Florida International University, enrolled in the course: Interactive Data Visualizations. As part of their coursework, these students wrote opinion essays reflecting on how they believe AI will shape their future careers. Their responses offer first-hand insight into the hopes, concerns, and expectations of emerging professionals as they prepare to enter an AI-influenced workforce. The guiding questions for their reflections include:

1. Have you personally experienced AI Anxiety? What is/was this like for you?
2. What's one thing about AI that makes you anxious?
3. What's one thing about AI that empowers you?
4. What did you learn about AI Anxiety through the data set you were provided?
5. How do you feel about the future of AI as it relates to your professional career?
6. Do you feel your college education should prepare you for AI in the real world?

7. On an optimistic note: How do you think AI can make the world a better place?

Bringing together insights from both the qualitative and quantitative data sets creates a strong foundation for future research on AI within the context of higher education (Mollick, 2024). The responses of the dissertation study from 398 individuals, each sharing personal reflections on both anxiety and empowerment related to AI, offer a window into the public's emotional landscape as this technology becomes more present in everyday life. Participants expressed a wide range of concerns, from fears about job displacement and privacy issues to appreciation for AI's efficiency and problem-solving potential. These contrasting perspectives reveal just how layered and complex people's relationships with AI truly are.

These initial observations point to a mix of hope and hesitation in how people view AI. There's a clear tension between concerns, including job loss and ethical risks, and the belief that AI can improve efficiency. This ambivalence opens the door for research that doesn't just highlight the benefits, or drawbacks, but thoughtfully examines both. For those shaping the future of AI, understanding and addressing this complexity is key to ensuring AI evolves in ways that reflect societal needs and values (Mollick, 2024)..

Digging deeper into the themes behind these concerns and benefits could help uncover what shapes public trust in AI. For instance, worries about job loss and economic disruption might be explored in parallel with how people view AI's potential to support learning and ethical decision-making. Insights like these could guide the development of practical solutions that make the technology more approachable while addressing key fears.

Using qualitative tools to analyze this data also opens the door to see how perceptions vary by age, education, or profession. That kind of insight could shape smarter education strategies, more responsive policies, and effective public outreach, ensuring that AI works for a wider range of people, not just a select few (Adetayo, 2024).

Bringing together insights from both past research and future studies can help shape a well-rounded approach to AI integration - one that balances its technical potential with the ethical, social, and economic factors influencing public opinion. Such a strategy could play a critical role in shaping policies and educational efforts that support a more informed and balanced understanding of AI (Walczak & Cellary, 2023).

In future research, it may also help to separate different kinds of anxiety, such as general anxiety, technology-related stress, and specific fears around AI, to better understand where it comes from and how it appears in different learning environments.

Looking ahead, this research doesn't just offer a clearer picture of how people view AI in various settings, it also equips us to respond more effectively to the real-world challenges and opportunities AI presents. As AI becomes increasingly embedded in how we work, learn, and live, these qualitative insights could be key to making informed decisions that help AI serve the broader good.

While a full analysis of this data is still to come, it holds strong potential for uncovering how people from various backgrounds perceive AI--both psychologically and socially.

## Conclusion

The Theory of Planned Behavior was proven as a solid framework for explaining how college students adopt AI in educational settings. It showed that students' attitudes, the influence of others, and their sense of control all play a major role in shaping their intention to use AI, which, in turn, influences how much they actually use it (Ajzen, 1991; Ajzen & Fishbein, 1980).

Behavioral intention emerged as a key bridge in the adoption process, linking students' thoughts about AI to their actual use of it. This supports Ajzen's Theory of Planned Behavior, which suggests that the move from evaluation to action largely happens through intention (Ajzen, 1991). The study points to the value of developing strategies that strengthen students' attitudes, social influences, and sense of control, all core elements of TPB, to encourage meaningful adoption of AI (Kim, 2002; Sanusi et al., 2024).

Contrary to expectations, AI anxiety did not alter the influence of attitudes, norms, or perceived control on adoption behavior. Instead, it had a more direct impact, acting as a standalone barrier to using AI (Huang, 2002; Tsai, 2020). This finding points to the importance of addressing anxiety head-on rather than treating it as something that simply interacts with other psychological factors. Supporting students' mental and emotional readiness may be just as critical as building their skills when introducing new technologies in educational settings (Dai et al., 2020; Wang et al., 2022).

To encourage more positive views of AI, educational programs should lean on proven strategies that highlight both its effectiveness and ethical applications. As Bates et al. (2020) note, integrating real-world examples of AI into the curriculum can help shift student attitudes in a favorable direction. Creating a classroom culture that openly supports AI use can also strengthen social norms around adoption, something educators and peers are well-positioned to influence (Kim, 2002; Mollick, 2024).

Helping students build confidence in using AI starts with equipping them with the right skills. Structured workshops and hands-on training (Adetayo, 2024; Venkatesh, 2012) not only improve technical know-how but also ease anxiety by making AI feel more approachable (Nazareno & Schiff, 2021).

Reducing AI-related stress is essential for successful integration in educational spaces. Beyond instructional methods, support systems like AI literacy programs and access to psychological counseling can help students navigate the stress that often comes with adopting new technologies (Almaiah et al., 2022; Gupta et al., 2023).

The impact of these findings reaches beyond the classroom. For meaningful change, both policymakers and technology leaders need to account for the psychological side of AI adoption. A forward-thinking strategy should combine strong technical infrastructure with a learning environment that supports mental and emotional well-being (Patel, 2024; Roetzer, 2022).

This dissertation adds meaningful perspective to the conversation around AI in higher education by examining how psychological factors shape students' ability to adapt to new technologies. It confirms the relevance of the Theory of Planned Behavior in educational settings and draws attention to the significant role AI anxiety plays in adoption decisions. To deepen our understanding and improve generalizability, future studies should consider exploring these patterns over time and in varied educational and cultural contexts (Chiarini, 2023; Jo, 2023).

Looking ahead, it's important that future research keep pace with the rapid evolution of AI. As technology advances, so do students' experiences with it. Longitudinal studies could offer valuable insight into how their attitudes and levels of anxiety shift over time as they grow more familiar with AI in the classroom (Fort & Voltero, 2004; Sindermann et al., 2021). Also, anxiety can be explored as more than just a background factor. It may play a central role in shaping how students form intentions and act. Instead of only asking whether anxiety blocks other influences, researchers can examine how it actively shapes students' readiness to engage with AI.

As AI becomes more pervasive, higher education must stay grounded not just in what students are doing, but also in what they are feeling. Supporting their emotional experience should not a side note; but rather foundational. While many students are enthusiastic about the possibilities of AI, just as many feel anxious, even afraid. They are stepping into a future that feels uncertain, and they need more than tactical tools and training. Mental health cannot be relegated to medical schools and dismissed by all other departments. Regardless of their major, when students are overwhelmed by self-doubt, their ability to learn is compromised. The educator’s role is to build learning environments that feel safe, supportive, and full of possibility. When both their fears and their dreams are honored, students can turn uncertainty into momentum. AI then becomes more than a skillset: It becomes the rocket fuel that helps students reach their goals and uplift the human spirit in the process.

REFERENCES


Abdaljaleel, M., Barakat, M., Alsanafi, M., Salim, N. A., Abazid, H., Malaeb, D., ... & Sallam, Abdaljaleel, M., Barakat, M., Alsanafi, M., Salim, N. A., Abazid, H., Malaeb, D., ... & Sallam, M. (2023). Factors influencing attitudes of university students towards ChatGPT and its usage: A multi-national study validating the TAME-ChatGPT survey instrument. *Research Square* https://doi.org/10.20944/preprints202309.1541.v1

Adetayo, A. J. (2024). Reimagining learning through AI art: the promise of DALL-E and MidJourney for education and libraries. *Library Hi Tech News*. https://doi.org/10.1108/LHTN-01-2024-0005

Ajlouni, A. O., Wahba, F. A. A., & Almahaireh, A. S. (2023). Students' attitudes towards using ChatGPT as a learning tool: The case of the University of Jordan. *International Journal of Interactive Mobile Technologies*, *17*(18). https://doi.org/10.3991/ijim.v17i18.41753

Ajzen, I., & Fishbein, M.(1980). *Understanding attitudes and predicting social behavior*. Prentice-Hall.

Ajzen, I. (1991). The theory of planned behavior. *Organizational behavior and human decision process*, *50*(2), 179-211. https://doi.org/10.1016/0749-5978(91)90020-T

Ajzen, I. (2005). *Attitudes, personality and behaviour* (2nd ed.). McGraw-Hill Education (UK).

Ajzen, I. (2006). Constructing a theory of planned behavior questionnaire.

Ajzen, I. (2012). The theory of planned behavior. In P. A. M. Lange, A. W. Kruglanski, & E. T. Higgins (Eds.), Vol. 1. *Handbook of theories of social psychology* (pp. 438-459). Sage.

Ajzen, I. (2015). The theory of planned behaviour is alive and well, and not ready to retire: A commentary on Sniehotta, Presseau, and Araújo-Soares. *Health Psychology Review*, *9*(2), 131-137. https://doi.org/10.1080/17437199.2014.883474

Ajzen, I. (2020). The theory of planned behavior: Frequently asked questions. *Human Behavior and Emerging Technologies*, *2*(4), 314-324. https://doi.org/10.1002/hbe2.195

Ajzen, I., & Klobas, J. (2013). Fertility intentions: An approach based on the theory of planned behavior. *Demographic Research*, *29*, 203-232.

Ajzen, I., Joyce, N., Sheikh, S., & Cote, N. G. (2011). Knowledge and the prediction of behavior: The role of information accuracy in the theory of planned behavior.

*Basic and Applied Social Psychology*, *33*(2), 101-117. https://doi.org/10.1080/01973533.2011.568834

Alzahrani, L. (2023). Analyzing students' attitudes and behavior toward artificial intelligence technologies in higher education. *International Journal of Recent Technology and Engineering (IJRTE)*, *11*(6), 65-73. https://doi.org/10.35940/ijrte.F7475.0311623

Bandura, A. (1977). Self-efficacy: Toward a unifying theory of behavioral change. *Psychological Review*, *84*(2), 191. https://doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (1982). Self-efficacy mechanism in human agency. *American Psychologist*, *37*(2), 122. https://doi.org/10.1037/0003-066X.37.2.122

Bandura, A. (1986). *Social foundations of thought and action: A social cognitive theory*. Prentice-Hall.

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

Bender, S. M. (2023). Coexistence and creativity: Screen media education in the age of artificial intelligence content generators. *Media Practice and Education*, *24*(4), 351-366. https://doi.org/10.1080/25741136.2023.2204203

Celik, I. (2023). Towards Intelligent-TPACK: An empirical study on teachers' professional knowledge to ethically integrate artificial intelligence AI-based tools into education. *Computers in Human Behavior*, 138, 107468. https://doi.org/10.1016/j.chb.2022.107468

Chai, C. S., Wang, X., & Xu, C. (2020). An extended theory of planned behavior for the modelling of Chinese secondary school students' intention to learn artificial intelligence. *Mathematics*, *8*(11), 2089. https://doi.org/10.3390/math8112089

Chen, L., Chen, P., & Lin, Z. (2020). Artificial intelligence in education: A review. *IEEE Access*, 8, 75264-75278. https://doi.org/10.1109/ACCESS.2020.2988510

Cheng, L., Umapathy, K., Rehman, M., Ritzhaupt, A., Antonyan, K., Shidfar, P., ... & Abramowitz, B. (2023). Designing, developing, and validating a measure of undergraduate students' conceptions of artificial intelligence in education. *Journal of Interactive Learning Research*, *34*(2), 275-311.

Chiu, T. K., Xia, Q., Zhou, X., Chai, C. S., & Cheng, M. (2023). Systematic literature review on opportunities, challenges, and future research recommendations of artificial intelligence in education. *Computers and Education: Artificial Intelligence*, 4, 100118.

Cooper, G., & Tang, K. S. (2024). Pixels and pedagogy: Examining science education imagery by generative artificial intelligence. *Journal of Science Education and Technology*, 1-13. https://doi.org/10.1007/s10956-024-10104-0

Cortez, P. M., Ong, A. K. S., Diaz, J. F. T., German, J. D., & Jagdeep, S. J. S. S. (2024). Analyzing Preceding factors affecting behavioral intention on communicational artificial intelligence as an educational tool. *Heliyon, 10(3), e25896.* https://doi.org/10.1016/j.heliyon.2024.e25896 Dai, Y., Chai, C. S., Lin, P. Y., Jong, M. S. Y., Guo, Y., & Qin, J. (2020). Promoting students' well-being by developing their readiness for the artificial intelligence age. *Sustainability*, *12*(16), 6597. https://doi.org/10.3390/su12166597

Derevyanko, N., & Zalevska, O. (2023). Comparative analysis of neural networks Midjourney, Stable Diffusion, and DALL-E and ways of their implementation in the educational process of students of design specialties. *Scientific Bulletin of Mukachevo State University.* Series "Pedagogy and Psychology, *9*(3), 36-44. https://doi.org/10.52534/msu-pp3.2023.36

Dinc, M. S., & Budic, S. (2016). The impact of personal attitude, subjective norm, and perceived behavioural control on entrepreneurial intentions of women. *Eurasian Journal of Business and Economics*, *9*(17), 23-35. https://doi.org/10.17015/ejbe.2016.017.02

Du Sautoy, M. (2019). The Creativity xode: Art and innovation in the age of AI. Harvard University Press. https://doi.org/10.2307/j.ctv2sp3dpd

Fernández-Batanero, J. M., Román-Graván, P., Reyes-Rebollo, M. M., & Montenegro-Rueda, M. (2021). Impact of educational technology on teacher stress and anxiety: A literature review. *International Journal of Environmental Research and Public Health*, 18(2), 548. https://doi.org/10.3390/ijerph18020548

Fernández-Prados, J. S., Lozano-Díaz, A., & Ainz-Galende, A. (2021). Measuring digital citizenship: A comparative analysis. *Informatics, 8*(1), 18. https://doi.org/10.3390/informatics8010018

Firat, M. (2023). What ChatGPT means for universities: Perceptions of scholars and students. *Journal of Applied Learning and Teaching*, *6*(1), 57-63. https://doi.org/10.37074/jalt.2023.6.1.22

Francis, J., Eccles, M. P., Johnston, M., Walker, A. E., Grimshaw, J. M., Foy, R., ... & Bonetti, D. (2004). *Constructing questionnaires based on the theory of planned behaviour: A manual for health services researchers*. Centre for Health Services Research.

Ghotbi, N., Ho, M. T., & Mantello, P. (2022). Attitude of college students towards ethical issues of artificial intelligence in an international university in Japan. *AI & Society*, 37, 283-290. https://doi.org/10.1007/s00146-021-01168-2

Gill, S. S., Xu, M., Patros, P., Wu, H., Kaur, R., Kaur, K., ... & Buyya, R. (2024). Transformative effects of ChatGPT on modern education: Emerging era of AI chatbots. *Internet of Things and Cyber-Physical Systems*, *4*, 19-23. https://doi.org/10.1016/j.iotcps.2023.06.002

Goldrick-Rab, S., & Cook, M. A. E. (2011). *College students in changing contexts. American higher education in the twenty-first century: Social, political, and economic challenges*, pp. 254-278. John's Hopkins University Press.

Graesser, A. C., Conley, M. W., & Olney, A. (2012). Intelligent tutoring systems. In K. R. Harris, S. Graham, T. Urdan, A. G. Bus, S. Major, & H. L. Swanson (Eds.), *APA educational psychology handbook, Vol. 3. Application to learning and teaching* (pp. 451–473). American Psychological Association. https://doi.org/10.1037/13275-018

Guan, F., Chen, J., Chen, O., Liu, L., & Zha, Y. (2019). Awe and prosocial tendency. *Current Psychology*, *38*, 1033-1041. https://doi.org/10.1007/s12144-019-00244-7

Gupta, D., Singhal, A., Sharma, S., Hasan, A., & Raghuwanshi, S. (2023). Humans' emotional and mental well-being under the influence of artificial intelligence. *Journal for ReAttach Therapy and Developmental Diversities*, 6(6s), 184-197.

Henry, S. (2025, April 8). Journalism advisory organizations issue rare alert to student news outlets: student media advisors modify long-standing advice in the wake of 'unprecedented' threats to student speech. *Nieman Reports.* https://niemanreports.org/student-journalists-press-freedom-splc/

Holmes, W., & Porayska-Pomsta, K. (Eds.). (2022). *The ethics of artificial intelligence in education: Practices, challenges, and debates.* Routledge.

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., ... & Kasneci, G. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences, 103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kim, H. (2002). Teachers' intention to use the Internet: an application of the theory of planned behavior using structural equation modeling (Doctoral dissertation, University of Georgia).

Kim, J., Kadkol, S., Solomon, I., Yeh, H., Soh, J. Y., Nguyen, T. M., ... & Ajilore, O. A. (2023). AI Anxiety: A Comprehensive Analysis of Psychological Factors and Interventions. *AI and Ethics.* http://dx.doi.org/10.2139/ssrn.4573394

Kim, J., Merrill, K., Xu, K., & Sellnow, D. D. (2020). My teacher is a machine: Understanding students' perceptions of AI teaching assistants in online education. *International Journal of Human–Computer Interaction*, 36(20), 1902-1911. https://doi.org/10.1080/10447318.2020.1801227

Kong, J. S., Teo, B. S., Lee, Y. J., Pabba, A. B., Lee, E. J., & Sng, J. C. (2021). Virtual integrated patient: An AI supplementary tool for second-year medical students. *The Asia Pacific Scholar,* 6(3), 87.

Li, J., & Huang, J. S. (2020). Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory. *Technology in Society*, 63, 101410. https://doi.org/10.1016/j.techsoc.2020.101410

Lim, T., Gottipati, S., & Cheong, M. L. (2023). Ethical considerations for artificial intelligence in educational assessments. In J. Keengwe (Ed.). *Creative AI tools and ethical implications in reaching and learning* (pp. 32-79). IGI Global Scientific Publishing. https://doi.org/10.4018/979-8-3693-0205-7.ch003

Lo, C. K. (2023). What is the impact of ChatGPT on education? A rapid review of the literature. *Education Sciences*, *13*(4), 410. https://doi.org/10.3390/educsci13040410

McNeal, L. (2019). Hush don't say a word: Safeguarding student freedom of expression in the Trump era. *Georgia State University law review, 35*(2), 251-298.

Merceron, A., Blikstein, P., & Siemens, G. (2015). Learning analytics: From big data to meaningful data. *Journal of Learning Analytics*, 2(3), 4-8. https://doi.org/10.18608/jla.2015.23.2

Mollick, E. (2024) *Co-intelligence: Living and working with AI.* Portfolio/Penguin.

Motlagh, N. Y., Khajavi, M., Sharifi, A., & Ahmadi, M. (2023). The impact of artificial intelligence on the evolution of digital education: A comparative study of openAI text generation tools including ChatGPT, Bing Chat, Bard, and Ernie. *arXiv, abs/2309.02029*. https://doi.org/10.48550/arXiv.2309.02029

Nazareno, L., & Schiff, D. S. (2021). The impact of automation and artificial intelligence on worker well-being. *Technology in Society*, 67, 101679. https://doi.org/10.1016/j.techsoc.2021.101679

Ngo, T. T. A. (2023). The perception by university students of the use of ChatGPT in education. *International Journal of Emerging Technologies in Learning (iJET)*, *18*(17), 4-19. https://doi.org/10.3991/ijet.v18i17.39019

Noor, N. M., Noranee, S., Zakaria, M. F., Unin, N., & Suaee, M. A. H. M. (2020, February). Online shopping: The influence of attitude, subjective norm and perceived behavioral control on purchase intention. In *Proceedings of the 2020 the 6th International Conference on E-Business and Applications* (pp. 33-36).

Patel, K. (2024). Ethical reflections on data-centric AI: Balancing benefits and risks. *International Journal of Artificial Intelligence Research and Development,* 2(1), 1-17.

Peart, M. T., Gutiérrez-Esteban, P., & Cubo-Delgado, S. (2020). Development of the digital and socio-civic skills (DIGISOC) questionnaire. *Educational Technology*

*Research and Development*, *68*, 3327-3351. https://doi.org/10.1007/s11423-020-09824-y

Peart, M., Cubo-Delgado, S., & Gutiérrez-Esteban, P. (2022). Exploring the role of digital and socio-civic skills for promoting youth participation and digital citizenship. *European Journal of Educational Research*, *11*(2), 697-709.

Pedro, F., Subosa, M., Rivas, A., & Valverde, P. (2019). Artificial intelligence in education: Challenges and opportunities for sustainable development. https://unesdoc.unesco.org/ark:/48223/pf0000366994

Peng, T. Q., Zhu, J. J., Tong, J. J., & Jiang, S. J. (2012). Predicting internet non-users' adoption intention and adoption behavior:: A panel study of theory of planned behavior. *Information, Communication & Society*, *15*(8), 1236-1257. https://doi.org/10.1080/1369118X.2011.614628

Rhoads, R. A. (2016). Student activism, diversity, and the struggle for a just society. *Journal of Diversity in Higher Education*, *9*(3), 189. https://doi.org/10.1037/dhe0000039

Roetzer, P., & Kaput, M. (2022) *Marketing artificial intelligence: AI, marketing, and the future of business*. BenBella Books, Inc.

Rovira, S., Puertas, E., & Igual, L. (2017). Data-driven system to predict academic grades and dropout. PLoS one, 12(2), e0171207. https://doi.org/10.1371/journal.pone.0171207

Sampson, E. E. (1967). Student activism and the decade of protest. *Journal of Social Issues*, *23*(3). https://doi.org/10.1111/j.1540-4560.1967.tb00584.x

Sanusi, I. T., Ayanwale, M. A., & Tolorunleke, A. E. (2024). Investigating pre-service teachers' artificial intelligence perception from the perspective of planned behavior theory. *Computers and Education: Artificial Intelligence*, 6, 100202. https://doi.org/10.1016/j.caeai.2024.100202

Strzelecki, A. (2023). To use or not to use ChatGPT in higher education? A study of students' acceptance and use of technology. *Interactive Learning Environments*, *32*(9), 5142-5155. https://doi.org/10.1080/10494820.2023.2209881

Tiwari, C. K., Bhat, M. A., Khan, S. T., Subramaniam, R., & Khan, M. A. I. (2023). What drives students toward ChatGPT? An investigation of the factors influencing adoption and usage of ChatGPT. *Interactive Technology and Smart Education, 21*(3), 333-355. https://doi.org/10.1108/ITSE-04-2023-0061

Tufekci, Z. (2013). "Not this one": Social movements, the attention economy, and microcelebrity networked activism. *American Behavioral Scientist*, *57*(7), 848-870. https://doi.org/10.1177/0002764213479369

Vázquez-Cano, E., Ramirez-Hurtado, J. M., Saez-Lopez, J. M., & Lopez-Meneses, E. (2023). ChatGPT: The brightest student in the class. *Thinking Skills and Creativity*, *49*, 101380. https://doi.org/10.1016/j.tsc.2023.101380

Vishnu, S., Sathyan, A. R., Sam, A. S., Radhakrishnan, A., Ragavan, S. O., Kandathil, J. V., & Funk, C. (2022). Digital competence of higher education learners in the context of COVID-19 triggered online learning. *Social Sciences & Humanities Open*, *6*(1), 100320. https://doi.org/10.1016/j.ssaho.2022.100320

Walczak, K., & Cellary, W. (2023). Challenges for higher education in the era of widespread access to Generative AI. *Economics and Business Review*, *9*(2), 71-100. https://doi.org/10.18559/ebr.2023.2.743

Wang, Y. Y., & Chuang, Y. W. (2024). Artificial intelligence self-efficacy: Scale development and validation. *Education and Information Technologies*, *29*(4), 4785-4808. https://doi.org/10.1007/s10639-023-12015-w

Wang, Y. Y., & Wang, Y. S. (2022). Development and validation of an artificial intelligence anxiety scale: An initial application in predicting motivated learning behavior. *Interactive Learning Environments*, *30*(4), 619-634. https://doi.org/10.1080/10494820.2019.1674887

Yilmaz, H., Maxutov, S., Baitekov, A., & Balta, N. (2023). Student's perception of Chat GPT: A technology acceptance model study. *International Educational Review*, *1*(1), 57-83. https://doi.org/10.58693/ier.114

Zhang, C., Schießl, J., Plößl, L., Hofmann, F., & Gläser-Zikuda, M. (2023). Acceptance of artificial intelligence among pre-service teachers: a multigroup analysis. *International Journal of Educational Technology in Higher Education*, *20*(1), 49. https://doi.org/10.1186/s41239-023-00420-7

APPENDICES

Measurement Instrument

| | | |
|---|---|---|
| **JESSICA KIZOREK** | | |
| Measurement Instrument | | |
| | | |
| **STUDENT DEMOGRAPHIC INFORMATION** | | |
| | | Gender |
| | | Age Range |
| | | Ethnicity |
| | | Country of Origin |
| | | College Location |
| | | College Major |
| | | |
| **STUDENT ATTITUDE TOWARDS USING AI IN COLLEGE** | | |
| | | I believe that generative artificial intelligence - text, image, and video - has arrived and is here to stay |
| | | AI is more useful than other sources of information that I have used previously in school |
| | | Using AI tools is a good idea in my university assignments and duties |
| | | Using AI tools is fun when it comes to my university assignments and duties |

| | | |
|---|---|---|
| | | I am enthusiastic about learning new technology for research |
| | R | I get bored quickly when using AI on schoolwork |
| | R | For me, AI is not a reliable source of accurate information |
| | | I believe that using AI can save time and effort in my university assignments and duties |
| | | I recommend AI to my colleagues to facilitate their academic duties |
| | | I believe I need to learn AI to prepare for my future in the workforce |
| | | I believe it's important for me to understand AI in order to make more money in life |
| | | I believe it's important for me to understand text-to-text generation (i.e. ChatGPT) |
| | | I believe it's important for me to understand text-to-image generation (i.e. DALL-E) |
| | | I believe it's important for me to understand text-to-video generation (i.e. Monet) |
| | R | I'd rather avoid AI if at all possible |
| | | |
| | | |
| **SOCIAL NORMS AROUND STUDENT USE OF AI IN COLLEGE** | | |
| | | My fellow schoolmates think using AI is a good idea when doing school work |
| | | I use AI tools because so many of my fellow school mates use it |

| | | |
|---|---|---|
| | | My college/university has encouraged me to us AI on projects and assignments |
| | | My college professors have encouraged me to us AI on projects and assignments |
| | | I have at least one professor who assigned us to AI in the classroom for assignments and projects |
| | R | I have at least one professor who has banned AI in the classroom for assignments and projects |
| | | Sometimes my schoolmates use AI sometimes when they are not supposed to |
| | | I know at least one student who has blatantly turned in plagiarized work created by AI |
| | R | My college/university has discouraged us to use AI on projects and assignments |
| | | I trust the opinions of my friends or colleagues about using ChatGPT |
| | | |
| | | |
| **PERCIEVED BEHAVIORAL CONTROL TOWARDS USING AI** | | |
| | | Given the resources, opportunities, and knowledge it takes to use AI tools, it would be easy for me to use AI tools. |
| | R | AI tools are not compatible with other systems I use. |
| | | I have complete control over whether I can use AI to complete school projects |
| | | I have the opportunity to use AI to complete projects |
| | | I have sufficient time available during class to use the AI to complete projects |

| | | |
|---|---|---|
| | | I've used AI in the past, so I can use AI in the future |
| | | I feel confident in using AI tools to finish school assignments |
| | | I have plenty of time outside of the classroom to use AI on homework and assignments |
| | | I have all the hardware I need in order to use the AI tools that interest me |
| | | I can afford to pay for the AI platforms I want to use (i.e. $20/month for OpenAI) |
| | | |
| | | |
| **STUDENT ANXIETY TOWARDS USING AI IN COLLEGE** | | |
| | | When it comes to completing schoolwork, learning to interact with an AI makes me anxious. |
| | | Being unable to keep up with the advances associated with AI in school makes me anxious. |
| | | I am afraid that AI techniques/products will increase their role in society. |
| | | I am afraid that if I begin to use AI techniques/products I will become dependent upon them |
| | | I fear AI tools are taking away my reasoning skills |
| | | Talking to friends/colleagues about AI techniques/products makes me anxious. |
| | | Getting error messages when operating an AI technique/product makes me anxious. |
| | | The way AI tools allows my classmates to cheat is distressing to me. |

| | | |
|---|---|---|
| | | I am afraid that an AI technique/product may make us even lazier. |
| | | I am afraid that AI techniques/products will replace someone's job. |
| | | I am afraid that it is necessary to use an AI technique/product in my job. |
| | R | I find using AI tools fun and easy when it comes to completing schoolwork |
| | | I am afraid of how smart and fast these new AI technique/product are |
| | | I am afraid that an AI technique/product may be misused |
| | | As a whole, I am afraid to use AI techniques and products |
| | | I am concerned that using ChatGPT would get me accused of plagiarism |
| | | I am concerned about the reliability of the information provided by ChatGPT |
| | | I am afraid that the use of the ChatGPT would be a violation of academic and university policies |
| | | I am concerned about the potential privacy risks that might be associated with using ChatGPT |
| | | I am afraid of relying too much on ChatGPT and not developing my critical thinking skills |
| | | I am afraid of becoming too dependent on technology like ChatGPT |
| | | |
| **STUDENT'S INTENTION TO USE AI IN COLLEGE** | | |
| | | I intend to use AI for school in the future |
| | | I plan to use AI tools for school more frequently |

| | | |
|---|---|---|
| | | I plan to learn new AI tools as they come out |
| | | I graduate soon, which will probably decrease my usage of AI in general |
| | | I intend to learn new AI platforms as I enter the workforce |
| | | |
| **STUDENT USE OF AI IN COLLEGE** | | |
| | R | I have never used AI tools for any use whatsoever (School, Work, Professional) |
| | R | I have never used AI tools to help me in my university assignments |
| | | I frequently use AI tools to help me with university schoolwork |
| | | I frequently use AI tools in other aspects of my life like Work, Personal, Pro-Social, Artistic |
| | | I am an early adopter when it comes to exploring the possibilities offered by new AI tools |
| | | I use AI almost daily in my assignments and duties as a college student |
| | | I use AI weekly in my assignments and duties as a college student |
| | | I use AI at least monthly in my assignments and duties as a college student |
| | | I have experience writing copy with generative AI (text-to-text i.e. ChatGPT) |
| | | I have experience making images with generative AI (text-to-image i.e. DALL-E) |
| | | I have experience making videos with generative AI (text-to-video i.e Monet) |

| | | |
|---|---|---|
| | | I love reading stories about AI in the news and on the internet |
| | | In general, I am obsessed with using AI |
| | | |
| **OPEN-ENDED QUESTIONS (QUALITATIVE)** | | |
| | | One thing that makes me feel anxious about artificial intelligence is ________________ |
| | | One thing that makes me feel empowered about artificial intelligence is ________________ |

FIU | Research & Economic Development
FLORIDA INTERNATIONAL UNIVERSITY

# MEMORANDUM

**To**: Dr. Amin Shoja

**CC:** Jessica Kizorek

**From:** Carrie Bassols, BA, IRB Coordinator ceb

**Date:** June 13, 2024

**Proposal Title:** "C56 - Kizorek - College Student's Adoption of AI"

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The Florida International University Office of Research Integrity has reviewed your research study for the use of human subjects and deemed it Exempt via the **Exempt Review** process.

**IRB Protocol Exemption #:** IRB-24-0299 **IRB Exemption Date:** 06/13/24
**TOPAZ Reference #:** 114304

As a requirement of IRB Exemption you are required to:

1) Submit an IRB Exempt Amendment Form for all proposed additions or changes in the procedures involving human subjects. All additions and changes must be reviewed and approved prior to implementation.
2) Promptly submit an IRB Exempt Event Report Form for every serious or unusual or unanticipated adverse event, problems with the rights or welfare of the human subjects, and/or deviations from the approved protocol.
1) Submit an IRB Exempt Project Completion Report Form when the study is finished or discontinued.

***Special Conditions:*** N/A

For further information, you may visit the IRB website at http://research.fiu.edu/irb.

VITA

JESSICA KIZOREK

Miami, FL 33161

| | |
|---|---|
| 2022 – 2025 | Doctoral Candidate<br>*Florida International University, Miami, FL*<br>*Dissertation Title*: Artificial intelligence in higher education: College students' AI anxiety as a moderating factor in technological adaptation |
| 2021 – 2022 | Master of Science - Global Strategic Communication<br>*Florida International University, Miami, FL* |
| 2020 | Online Certificate - Artificial Intelligence for Growth<br>*Northwestern University: Kellogg School of Business, Chicago, IL* |
| 1998 – 2003 | Bachelor of Science - Spanish for the Professions, Business minor<br>*University of Colorado, Boulder, CO* |
| 2024 | Adjunct Professor – Fall 2024<br>*Florida International University, Miami, FL* |
| 2025 – Present | Visiting Professor – Spring 2025 – Fall 2026<br>*Florida International University, Miami, FL* |
| 2001 – Present | President, *Two Parrot Productions, Miami, FL* |
| 2015 – Present | Executive Director, *Eyes On Your Mission, Miami, FL* |
| 2010 – Present | Creator, *Badass Businesswomen, Miami, FL* |