THE INFLUENCE BATTLE: HOW PERCEIVED RISK, ORGANIZATIONAL TRUST, AND SOCIAL INFLUENCE SHAPE EMPLOYEE INTENTIONS TO ADOPT AI

by

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ABSTRACT

MICHAEL M. MUSAU. The Influence Battle: How Perceived Risk, Organizational Trust, and Social Influence Shape Employee Intentions to Adopt AI. (Under the direction of DR. REGINALD SILVER)

Objectives: The adoption of Artificial Intelligence is influenced by a myriad of factors including employees' perceived risk acting as a salient barrier to AI adoption in organizations. Numerous prior studies, grounded in acceptance frameworks, have focused on individual level psychological determinants that impact adoption. This study examines the direct effect of perceived risk, social influence, and organizational trust on behavioral intention to adopt AI and to what degree social influence and organizational trust influence the effects of perceived risk in AI adoption intent.

Methods: Using validated scales, a quantitative online survey was administered to employed adults in the United States across multiple industries and organizations. Using Partial Least Squares Structural Equation Modeling (PLS-SEM), the data was analyzed to determine the resulting direct relationships between perceived risk, social influence, organizational trust and behavioral intention to adopt AI and test the interaction effects for the proposed moderators.

Results: Observed results indicated perceived risk is negatively associated with behavioral intention to adopt AI, while social influence positively impacted behavioral intention to adopt AI. The interaction effect between social influence and perceived risk was statistically significant indicating that social influence attenuates the negative association between perceived risk and behavioral intention. In contrast, organizational trust did not significantly influence behavioral intention to adopt AI and did not significantly moderate the relationship between perceived risk and behavioral intention. The model explained 43.9% of the variance in behavioral intention to adopt AI ($R^2 = 0.439$) and exhibited strong predictive relevance ($Q^2 = 0.411$).

Conclusion: The results of this study reinforce the negative impact of perceived risk towards AI adoption intentions and highlights social influence as a key factor shaping employees perceptions of risks associated with AI and their intentions to use the technology. Organization leaders may improve adoption outcomes by reducing perceived risks through targeted communications, training, and proper governance practices while targeting credible social referents to support AI adoption. The non-significant results of organizational trust influence warrant further investigation.

Keywords: Artificial Intelligence, Perceived Risk, Social Influence, Organization Trust, Behavioral Intention, UTAUT, PLS-SEM.

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DEDICATION

I dedicate this dissertation to my family. Your encouragement, patience, and unwavering support provided the strength that sustained me throughout this journey. Your belief in me made the completion of this work possible.

TABLE OF CONTENTS

LIST OF TABLES

LIST OF FIGURES

CHAPTER 1: INTRODUCTION

Change is not only essential but also inevitable for any organization striving to improve their performance, and, for many years, technology has been used as a catalyst for organizational transformation. The introduction of artificial intelligence (AI) has, not only created a disruption in how we conduct business but has also introduced discomfort to many people who are fearful of the impact of the technology. AI, defined as the use of computer software and systems to emulate human cognitive processes (Kumar et al., 2023) like learning, interacting, and problem solving (Raisch & Krakowski, 2021), is seen as a dominant catalyst of technological change. This emerging technology has the potential to revolutionize all areas of our lives (Gerlich, 2023). The rapid growth of AI has been facilitated by the availability of large amounts of data, the increased affordability and accessibility of computation power, storage technologies, improvements in machine-learning techniques, and the availability of open-source machine-learning packages (Kumar et al., 2023).

As a technology that was created to assist and improve the quality of life for humans (Gerlish, 2023), AI is impacting society at large not just the business environment. This technology offers great benefits for efficiency enhancement while introducing trust related technology risks like data privacy (Bankins & Formosa, 2023, Richardson et al., 2021) and economic turbulence especially within industries that require less creativity and involve repetitive tasks (Nah et al., 2023; Eftimov & Kitanovikj, 2023). AI is like a double-edged sword, some people believe it is bound to result in an unfavorable impact to society while others favor its development and use (Schwesig, 2023). In using this emerging technology, firms can benefit from cost savings and enhanced efficiency that the AI systems generate as they improve speed of execution and accuracy (Arora et al., 2023; Fang et al., 2021; Wang et al., 2023). Within the healthcare industry, as an example, benefits from cost savings, faster and more accurate diagnoses, and treatment options (Fang et al., 2021) impact the organization, the medical practitioners and the patients. This coexistence of potential benefits and risks warrants and motivates researchers to further investigate this emerging technology. Empirical evidence can inform practitioners on adoption approaches that maximize the value while reducing organizational and individual level risks.

Given AI's potential to reshape business operations and employee work practices, it is critical for management and stakeholders to understand the employees' behavioral intentions (BI) of AI adoption and its use for a variety of reasons; First costs; implementing the technology often requires a substantial investment by the organization (P. Kumar et al., 2023; Chaibi & Zaiem, 2022). Therefore, understanding the impact of introducing the technology to the organization can help the organization better calculate their return on investment, whether the technology will pay off and when or if it would lead to undesired losses. Second, understanding the employees' BI will allow for a smoother transition process when the technology is introduced to the organization, assisting in workforce change management. Third, identifying the key antecedents of BI, including risk-related concerns, can guide HR and leadership decisions related to job design, training, and employee support during AI-enabled work redesign (Eftimov & Kitanovikj, 2023). And fourth, understanding employees' intentions of adoption could help the organization identify the factors that increase or decrease adoption chances, and work on intervention mechanisms to drive increased adoption within the organization (Giudice et al., 2023).

Behavioral intention refers to the willingness or readiness of an individual in engaging in a specified behavior (Pavlou, 2003). Consistent with technology acceptance research, behavioral intention is typically theorized to translate into subsequent use behavior and empirical studies report a positive association between intention and actual use (Cabrera-Sánchez, 2021; Uymaz et al., 2024). In the context of AI, the behavioral intention (BI) to adopt AI has also been assessed to positively correlate with the actual use of AI (L. Eftimov and B. Kitanovikj, 2023). Researchers, drawing on multiple theoretical perspectives, have examined behavioral intention to adopt technology and identified a range of antecedents that shape individuals' adoption intentions. For example, the theory of planned behavior (Ajzen, 1991) posits that the behavioral intentions are influenced by perceived behavioral control, subjective norms, and attitudes which in turn predict the actual behavior of the subjects (Pavlou, 2003). In using the Unified Theory of Acceptance and use of Technology (UTAUT), researchers have confirmed that perceived usefulness of technology, ease of use, social influence, and facilitating conditions are all strong influencers of BI in the adoption of technology (Venkatesh et al., 2003; Venkatesh et al., 2012). This study adopts UTAUT as its theoretical framework because it integrates key determinants from multiple established technology adoption model, making it a comprehensive framework for explaining behavioral intention in organizational settings. Using UTAUT to anchor the model, we examine social influence as a key contextual determinant of AI adoption intention and supplement the framework with perceived risk and organizational trust to capture concerns and organizational conditions that may strengthen or weaken employees' intention to adopt AI.

Developed by Venkatesh et al. (2003), UTAUT integrates key determinants from multiple prior technology acceptance models into a single, comprehensive framework which demonstrates strong explanatory power for behavioral intention and technology use across a wide range of contexts. In its original form, UTAUT posits that performance expectancy, effort expectancy, and social influence shape behavioral intention, while facilitating conditions support actual use, with these relationships varying by factors such as age, gender, and experience (Venkatesh et al., 2003). Building on this foundation, the present study leverages UTAUT's social influence mechanism and extends the model by incorporating perceived risk and organizational trust to better capture concerns and organizational conditions that may shape employees' AI adoption intentions.

The perception of risk, as defined by Goh et al. (2024), is the individual's subjective assessment or understanding of potential uncertainties associated with a particular situation of activity. Over the years, the term perceived risk has been accorded various definitions. For example, risk perception has been defined as the individual's assessment of risk inherent in a particular situation by Baird and Thomas (1985), while Bauer (1967) defined perceived risk as the individual's perception of the uncertainty associated with a particular behavior. Uncertainty alludes to lack of sufficient knowledge about a phenomenon which drives the individual's desire to avert interacting with the object or subject. Risk perception is influenced by various factors including personal experiences, emotions, cultural norms and trust (Krieger et al., 2024). The perception may also be influenced by how much the individual is familiar with the subject, subsequently, if they perceive risk, they may seek information about the subject through formal and informal channels. Risk perception may also result from one's assessment of previously related events. The associated risk influences the perception of the situation, available options and the eventual decision (Williams and Noyes, 2007). Risk perception may lead the employees to find specific technologies or aspects of the technologies undesirable and hinder them from embracing the technologies. This study adopted the definition of perceived risk as an individual's subjective anticipation of a potential negative outcome or consequence associated with their intention to adopt Artificial Intelligence technology (Featherman & Pavlou, 2003; Hsu & Lee, 2023; Nagy et al., 2024). The complexities associated with AI adoption necessitate the systematic study of perceived risk, a multi-dimensional construct, and its relationship with employees' behavioral intention to adopt artificial intelligence.

Social influence is the degree to which an individual's behavior is determined by how other people perceive them (Wang, 2022). In technology adoption studies, social influence refers to the extent to which an individual perceives how other people see them act towards the adoption of a technology (Xu et al., 2017). Social influence has also been defined as the extent to which an individual's decision to accept and use a technology has been swayed by important others (Carter et al., 2020). These people, important others, that appear to exert pressure on the individual include, colleagues, family members and friends (Wang, 2022, Xu et al., 2017). In the advent of emerging technology, social media, digital prints, and news channels act as additional sources of social influence to an individual. Social influence is not only the individual's perception of the opinion the important others within their circles hold, but also their recommendations and behaviors which may lead to peer group pressure, the pressure the individual feels to conform to the group resulting in change of behavior (Eckhardt, 2009). Social influence is a major construct that directly influences employees' behavioral intention towards the adoption of technology (Venkatesh et al.,2003). The study by Eckhardt et al. (2009) examined the role of social influence among both adopters and non-adopters of technology. The findings revealed that non-adopters were more heavily influenced by their peers in their decision not to adopt, compared to the social influence experienced by adopters. This highlights the criticality of examining the impact of social influence on the adoption of Artificial Intelligence. For organizations to maximize the return on technology investments, management teams must be equipped with the tools and knowledge to assess such influences within their workforce and implement strategies that foster successful adoption. The study of social influence and how it impacts employees helps us to understand more about the behavioral intention of adoption of AI. Understanding social influence also gives us further insights into the various voices that employees, as individuals, must deal with as they make decisions on their intention to adopt technology. This study examined social influence as the external voices, excluding influence from organization leadership teams, that shape the employees' behavioral intention to adopt AI, operating through influence processes such as compliance with subjective norms, identification with social groups and their image benefits, and internalization of shared beliefs.

Employees seek information from various sources including their organization management teams. If an employee is willing to rely on information provided by people with the responsibility of making decisions in their organization, it means they have trust in the organization (Huurne & Gutteling, 2008). Trusting another person, group or entity, such as a management team, requires an assessment of their competence, integrity, and benevolence, while also considering the potential losses, should the trust be betrayed (Bachmann & Inkmen, 2011). In instances of uncertainty, employees look to lean on a trusted party, one that demonstrates ability / competence, integrity in their actions and shows care and concern (is benevolent) as a source of information. Trust also entails a judgment of similarity of intentions or values (Siegrist et al., 2005) ergo each employee may have a different perception or degree of organizational trust based on their assessment of the organization leadership's competency and values. Trust promotes risk taking (Schoorman et al., 2007), suggesting that as organizational trust increases, employees are likely to engage in risk taking behaviors as part of their participation in the organization. Trust empowers employees to form new networks, take calculated risks, and rely on one another's capabilities in pursuit of high-performance outcomes (Shockley-Zalabak et al., 2000; Schoorman et al., 2007). Organizational trust has the potential to increase firm performance and increase competitive advantage. When employees believe in the competence, integrity, and benevolence of their colleagues and leadership, they are more willing to engage in behaviors that go beyond individual success, contributing to a culture of winning together. As members of an organization identify with the organization, they are proud to be associated with the brand and carry it with pride which leads to the organization brand benefiting as its ambassadors carry its flag wherever they go (Shockley-Zalabak et al., 2000). In such environments, organizational trust becomes a strategic asset, enhancing adaptability, innovation, and sustained competitive advantage in increasingly uncertain and dynamic business contexts (Liu et al., 2025). This study adopted the definition of organizational trust as the employee's willingness to accept vulnerability and take risks based on the positive expectations of the organization's leadership team's competence, integrity and benevolence as they make decisions and perform organizational actions (Shockley-Zalabak et al., 2000; Liu et al., 2025; Schoorman et al., 2007). This would reflect the belief that the leadership team is expected to act reliably, ethically and with concern and care towards their employees especially in times on uncertainty.

The adoption of AI research has evolved from Information Systems (IS) research which has long studied the why and how individuals adopt new technologies (Venkatesh et. al., 2003). This led to development and use of numerous research models being used to measure different aspects of adoption, including (i) individual acceptance, (ii) organizational level adoption, and (iii) task technology fit (Venkatesh et. al., 2003). According to several studies conducted in the last two decades, the use of technology due to behavioral intention is the most utilized feature in researching the acceptance of technology (Almarzouqi, et al., 2022) and the most utilized models used for the research are Unified Theory of Acceptance and Use of Technology (UTAUT)

(Venkatesh et al.,2003) and Technology Adoption Model (TAM) (Davis, 1989). UTAUT is a comprehensive theory that incorporates eight technology acceptance theories, namely, the Technology Acceptance Model (TAM), Theory of Reasoned Action (TRA), Motivation Model (MM), Theory of Planned Behavior (TPB), Combined TAM and TPB (C-TAM-TPB), Model of PC Utilization (MPCU), Innovation Diffusion Theory (IDT), and Social Cognitive Theory (SCT) (Venkatesh et al., 2012). In the initial UTAUT study results by Venkatesh et al. (2003), the adjusted R-squared values for the eight models comparing the intention to use information technology ranged from 0.17 to 0.53. However, UTAUT showed an adjusted R-squared value of 0.69, indicating that the UTAUT model had a higher explanatory power of the variance in technology use intention compared to the other eight models individually (Jin and Ahn, 2019). The original version of UTAUT was developed to study technology adoption for employees within organizations. The model contained four main constructs: i) Performance Expectancy (degree of benefit realized by users), ii) Effort Expectancy (degree of ease of use), iii) Social influence (perception by others), and iv) Facilitating Conditions (perceptions of resources and support available to perform a behavior) (Venkatesh et al., 2012). By extending and incorporating additional constructs like hedonic motivation, price value and habit to the existing UTUAT framework Venkatesh et al., (2012) developed UTAUT2 which has been widely used in the study of technology acceptance by consumers in various industries. Both UTAUT and UTAUT2 have been used to study behavioral intentions to adopt AI by employees and consumers across multiple industries, for example healthcare, education, finance, and automotive. This study used UTAUT, considering its robustness in explaining technology acceptance and use, as its main theoretical framework.

Perceived risk is the process of evaluating an object or information associated with something, interpreting it, and forming an opinion about the severity of the potential consequences associated with the object (Mayer, 1995). Perceived risk leads to feelings of uncertainty about technology and may induce a negative behavior towards the adoption of AI as indicated in previous studies (Chaudhury, 2022; Hsieh, 2023; Huang et al., 2023; Prakash & Das, 2021). As people seek knowledge to counter the perceived risk, they may rely on voices of reason that surround them, these may include from their social groups or what has been presented by their organization. In the existing literature, it is not evident which source of information seems to influence the affected employee more at the workplace. This research extends the existing literature by introducing moderating relationships to the direct effect relationship between perceived risk and behavioral intention to adopt AI. As a potential voice of influence, research about organizational trust in relation to behavioral intention in the adoption of Artificial Intelligence has received limited attention, this study aims to evaluate the moderating effects of organizational trust and social influence in the relationship between the employees perceived risk of AI and their behavioral intention to adopt AI. This study also seeks to understand which voice, if any, is more influential or dissenting, to the employees with a perceived risk of AI in their behavioral intention to adopt the technology. In essence, which voice is louder, the employees' social groups or the organization leadership team? Findings from this study have important managerial decision-making implications in the implementation of AI in organizations. It is anticipated that managerial teams will find this knowledge useful as they make decisions to improve technology acceptance and utilization.

The remainder of this document is organized as follows. The next chapter provides a review of the extant literature on artificial intelligence and how it has evolved over the years since its inception. It also provides a review of the framework used for this research, Unified Theory of Acceptance and Use of Technology and the focal constructs studied, behavioral intention to adopt AI, perceived risk, social influence, and organizational trust. This literature review chapter closes with development of the 5 hypotheses specifying the proposed relationships among these constructs. Chapter 3 describes the research design, including the sample, measurement scale, data collection procedures, and analytical approach. Chapter 4 presents the results of the empirical analyses. The final chapter discusses the results, outlines theoretical and practical implications, acknowledges study limitations, and concludes with future research recommendations.

CHAPTER 2: LITERATURE REVIEW AND HYPOTHESES DEVELOPMENT

Literature Review

AI Lit Review

The concept of improving computing systems to reason like humans has been around for nearly eighty years. In 1945, Vannevar Bush proposed a system that amplified the knowledge and understanding of people. A few years later, Alan Turing, using an imitation game, explained the mathematical possibility of artificial intelligence in 1950 when he published the seminal article "Computing Machinery and Intelligence" (Haenlein & Kaplan, 2019). Turing (1950) suggested that systems that can store information can be trained to execute instructions using logic to make decisions or solve problems. In July of 1956, John McCarthy and Marvin Minsk hosted an AI conference at Dartmouth University that brought together renowned scientists of the time including Alexander Simon, Allen Newell and John Shaw, the inventors of the Logic Theorist (Haenlein & Kaplan, 2019). It was during this conference that the words Artificial Intelligence were introduced (Haenlein & Kapl 2019).

Despite the publicized issues of AI systems, like racial and gender bias (Samorani et al., 2022), or data privacy and security risks (Bankins & Formosa, 2023), this innovative technology has plenty to offer and promises significant advancements and improvements to corporations. However, for the organizations to realize benefits from their investment of this emerging technology, its intended users must embrace and adopt it (Yi et al., 2006). AI is expected to increase productivity, increase efficiency, realize significant cost savings, increase revenue and subsequently, improve firm performance (A. Kumar et al., 2023; Gerlich 2023). Internet growth has spurred organizations to advance their offerings to reach more customers with the use of web-based applications (Martins et al., 2014). By using AI scheduling and patient flow prediction systems, hospitals can reduce overtime costs (Wang et al., 2023) and reduce burnout rates for their team members. By improving resource planning, organizations can also schedule resources when necessary to attend to their customers giving them organized work schedules (Bertsimas et al., 2022). The use of technology driven services can be the initiation of a long-term relationship between organizations and their end customers (Featherman & Pavlou, 2003). This implies technology adoption is not a one-time discussion in an organization but rather should be an ongoing discussion amongst the leadership teams. Organizations put a lot of investments, time and effort, into technology with the hope of achieving competitive advantages (Eckhardt et al., 2009).

AI systems are broadly categorized into two types of systems; Automation-Based Systems, those that take over tasks currently being done by humans and Augmentation-Based Systems, those that are built to help humans accomplish complex tasks like data analysis and decision making (Einola & Khoreva, 2023). The nature of the task or the use case should determine whether an organization would opt for either automation, augmentation, or both as their strategy (Raisch & Krakowski, 2021). A three-way choice emerges in the literature whether to select an autonomous system, augmentation system, or both. Decision makers need to be cognizant that the different stakeholders have different perceptions of AI systems and how they should incorporate AI into the organizations (Einola & Khoreva, 2023). Managements' primary objective is improving efficiency and increasing cost reductions, which calls for automation, to take over repetitive tasks and either reassign the employees or let them go, leading to loss of skilled labor (Raisch & Krakowski, 2021). Automation strategies are likely to exacerbate employees fears of being displaced or losing their jobs to the AI systems (P. Kumar et al., 2023; Raisch & Krakowski, 2021). The desire to improve efficiency and reduce costs may appear tempting as a motivator to opt for an automation-based AI system but according to A. Kumar et al. (2023), prior research indicates profits decline when employees are laid off after an AI system implementation. This presents the management stakeholder team with the paradox of adopting automation or augmentation-based AI systems (A. Kumar et al., 2023). On one hand, automation increases cost savings as it increases efficiency and arguably reduce human errors (Arora et al, 2023; Nenova & Shang, 2022) while on the other hand an augmentation strategy leads to the improvement of effectiveness of AI-Based interventions by combining them with human expert opinions, increasing their algorithmic transparency and emphasizing their genuine care and warmth (Kyung & Kwon, 2022). It also helps in improving decision making and reducing error rates (P. Kumar et al., 2023) leading to improved performance and superior efficiency (Lebovitz et al., 2022). In the medical industry, AI is more appealing to patients when it is used in conjunction with a human expert (Longini et al., 2019), consequently, a strategy that allows both types of systems to be incorporated may offer the best benefit to the firms and the industry. Automation and augmentation are interdependent, interacting in similar or closely related tasks (Einola & Khoreva, 2023). AI is shaped by Humans through daily choices, actions, and interactions by defining objectives, setting constraints, generating, and choosing training data and providing AI with feedback while AI shapes human behavior by informing, guiding, and steering human judgement (Einola & Khoreva, 2023). Given the advantages realized when types of systems are used, healthcare organizations should adopt a strategy of both automation and augmentation (Raisch and Krakowski, 2021).

Owing to its impact and potential to change the landscape of technology, AI adoption studies cut across many sectors and industries. In the Human Resources area, AI is expected to revolutionize and streamline the hiring process (Figueroa-Armijos et al., 2023). In the automotive industry, manufacturers are developing driverless cars that use AI (Davenport et al., 2020). Research in the marketing sector identifies the biggest use of AI being in retail, banking, consumer packaged goods, and travel (Davenport et al., 2020). Within the healthcare industry, according to Longini et al. (2019), evidence of AI use is seen as early as the 1970s being utilized in diagnosis and decision-making applications. AI applications are used to mimic the decision-making abilities of human experts in the specific medical domains using rule-based algorithms to analyze patient data and provide recommendations (Longini et al. 2019). In the 1980s and 1990s more complex AI applications like neural networks and machine learning systems gained popularity within the healthcare industry (Longini et al. 2019). Diagnostic radiology, one of the most popular AI applications, has been in use since the 1980s, although it was limited in its use initially due to technical limitations (Lebovitz et al., 2021). Since then, there has been an explosion of AI applications development and use. As of June 2021, the US Food and Drug Administration (FDA) had authorized over 300 AI based medical devices (Dai & Tayur, 2022).

Within different organizations, some employees have fears and concerns towards the adoption and use of AI. Among the leading fears, data security concerns revolve around the possibility of data breaches and privacy violations (Laiet al., 2024; Schwesig, 2023) which is enhanced with the practice of large-scale data collection without explicit consent (Lai et al., 2024). Lack of transparency and opacity of the AI systems evokes apprehensions for use of the system also (Bankins & Formosa, 2023). Unclear accountability especially around who is responsible in case of errors (Figueroa-Armijos et al., 2023) increases anxiety and propagates fears. Social and ethical concerns associated with biases, systemic discrimination, injustices, and unfair treatment resulting from flawed algorithms and poor data quality contribute to AI adoption fears (Gerlich, 2023). In addition, fears arising from job displacement, due to automation, intensify anxieties associated with job securities (Gerlich, 2023; Figueroa-Armijos et al., 2023) and may result in rejection of the technology. Innovation inherently disrupts established norms and workflows, prompting necessary adjustments within organizations (Ram & Sheath, 1989). When organizations underutilize technologies like AI, they risk substantial financial losses, diminished returns on their investment and poor efficiency gains in their processes (Maruping et al., 2017). Technologies meant to improve productivity must be accepted and utilized by employees (Venkatesh et al., 2003). Given the competitive pressures in most industries, remaining competitive is not an option but a necessity for organizational success and sustainability (Gerlich, 2023). Change is inevitable but it may not always be well received because of perceived fears and risks. When individuals encounter innovative technologies, they will either, adopt, postpone or reject the technology (Laukkanen, 2016). This resistance to emerging technology by some, although natural, underscores the necessity of understanding genuine user perceptions and underlying drivers influencing technology adoption decision (Martins et al., 2014).

Taken together, the breadth of AI applications across industries and the persistent concerns employees express, such as privacy, security, transparency, accountability, and job displacement, underscore that AI adoption is not determined by technical capability alone but also by employees' perceptions and intentions. Because organizational value from AI depends on employee acceptance and sustained use, a theoretically grounded framework is needed to explain why individuals choose to adopt, postpone, or reject new technologies. Accordingly, the next section introduces the Unified Theory of Acceptance and Use of Technology (UTAUT) as the study's foundational adoption framework and motivates its suitability for examining behavioral intention in organizational settings, before extending it with perceived risk and organizational trust to better capture AI-specific concerns.

Unified Theory of Acceptance and Use of Technology

The use of theories, models and frameworks in technology adoption studies serve several purposes, primarily to understand, explain and predict how individuals accept and use new technologies and systems (William et al., 2015; Chau, 1996; Venkatesh et al., 2003; Venkatesh et al., 2012). Theories, models and frameworks are also used to harmonize existing research by bringing together various theories and providing robust and comprehensive frameworks, which, in the absence of the harmonization, creates confusion for researchers when deciding what theories and measurements to use for research (William et al., 2015; Venkatesh et al., 2016). A great example is the Unified Theory of Acceptance and Use of Technology (UTAUT), which was formulated by combining various constructs and measurements from previously documented theories used in technology adoption (Venkatesh et al., 2003). Some models are used for explaining and predicting user behavior by identifying the fundamental determinants of users' intentions to use a new technology and the actual usage behavior (Brown et al., 2002; Davis, 1989). Another use is guiding practitioners and management teams on implementation studies by helping them develop actionable interventions to enhance technology adoption and utilization (Venkatesh et al., 2003; Venkatesh & Bala, 2008; Blut et al., 2022; Chau, 1996). Existing theories are continuously extended to expand the existing knowledge and theoretical boundaries through the incorporation of new constructs or even examining different target populations (Venkatesh et al., 2012), for example UTAUT 2 was formulated as an extension of UTAUT by adding new constructs and examining consumers as the target population (Venkatesh et al., 2012; Venkatesh et al., 2016). Theories and models are thus a fundamental component of empirical studies that allow for a structured and systematic process of analysis and inference.

Studies examining the intention to use and actual use of technology in organizational contexts have evolved over the years through using different theories to investigate the drivers and influencers of technology adoption. In the Theory of Reasoned Action, (Fishbein & Ajzen, 1975), a fundamental and influential theory of human behavior originating from social psychology (Venkatesh et al 2003; Dwivedi et al., 2019), Fishbein & Ajzen (1975) argued that the behavior of an individual is driven by their intended behavior which is a function of their attitude or opinion toward that behavior and subjective norms. Theory of Planned Behavior, TPB, (Ajzen, 1991), was developed as an extension of TRA by adding the perceived behavioral control which accounted for situations where the subject of study did not have some or total volitional control (Chau & Hu, 2002; Lai, 2017, Venkatesh et al., 2003; Dwivedi et al., 2019). Technology Adoption Model, TAM, (Davis, 1989), was developed as a derivative of TRA and was specifically created to be used in the context of information system acceptance and use (Venkatesh et al.,2003; Lai, 2017). Innovation Diffusion Theory, IDT, (Rogers 1995), also rooted in sociology, posits that the use of technology was communicated over time through amongst members of social systems through channels (Venkatesh et al., 2003; Dwivedi et al., 2019). Other theories used in the study of technology adoption include: Social Cognitive Theory, SCT, (Compeau et al., 1999) which is used to explain human behaviors in technology adoption focusing on factors like self-efficacy (Venkatesh et al., 2003), Model of PC Utilization, MPCU, (Thompson et al., 1991) that was developed to predict use of personal computers (Venkatesh et al., 2003), Motivational Model, MM, (David et al., 1992) which was developed to focus on intrinsic and extrinsic motivations for technology adoption (Venkatesh et al., 2003), Technology Adoption Model 2, TAM2, (Venkatesh & Davis, 2000) an extension of TAM that included social influence and cognitive processes as antecedents (Lai, 2017), Technology Adoption Model 3, TAM3 (Venkatesh & Bala, 2008) was developed to unify TAM2 and determinant of perceived ease of use that were developed by Venkatesh & Davies (2000), (Lai, 2017), Unified Theory of Acceptance and Use of Technology (UTAUT) was developed through a processes of synthesizing previously established models (Venkatesh et al., 2003), and Unified Theory of Acceptance and Use of Technology revision 2, UTAUT2 (Venkatesh et al.,2012) which was developed as an extension of UTAUT by adding constructs and variables that would be useful for studying consumers (Venkatesh et al., 2012).

UTAUT was developed by Venkatesh et al., (2003) after systematically reviewing the existing literature on acceptance models, identifying eight of the prominent and widely used models for technology adoption, examining the performance of these eight models and theories using data from four companies to establish a baseline for their explanatory power individually. The process culminated in the synthesis of eight models/theories, namely: TRA (Fishbein & Ajzen, 1975), TAM (Davis, 1989), TPB (Ajzen, 1991), MM, combined TAM & TPB model, C-TAM-TPB, (Taylor & Todd, 1995), MPCU (Thompson et al., 1991), IDT (Rogers 1995), and SCT (Compeau et al., 1999), to formulate the integrated UTAUT (Venkatesh et al., 2003). The UTAUT model identified and used three predictors of Behavioral Intention (BI) to adopt technology: social influence, performance expectancy, and effort expectancy. (Venkatesh eta l., 2003). Additionally, behavioral intention and facilitating conditions were identified as significant indicators of actual technology usage in organization environments (Venkatesh eta l., 2003; Maruping et al., 2017). Venkatesh et al. (2003) also identified age, gender, voluntariness, and experience as variables that moderated the relationship between the predictor variables and the dependent variables. The combined model, UTAUT, was found to have a stronger explanatory power compared to the individual models (Venkatesh et al. 2003; Martins et al., 2014; William et al., 2015; Dwivedi et al., 2019). Venkatesh et al. (2003) developed UTAUT with the intention of harmonizing existing literature and theories used in the adoption research (William et al., 2019). Below is an image of the original UTAUT model proposed by Venkatesh et al. (2003).

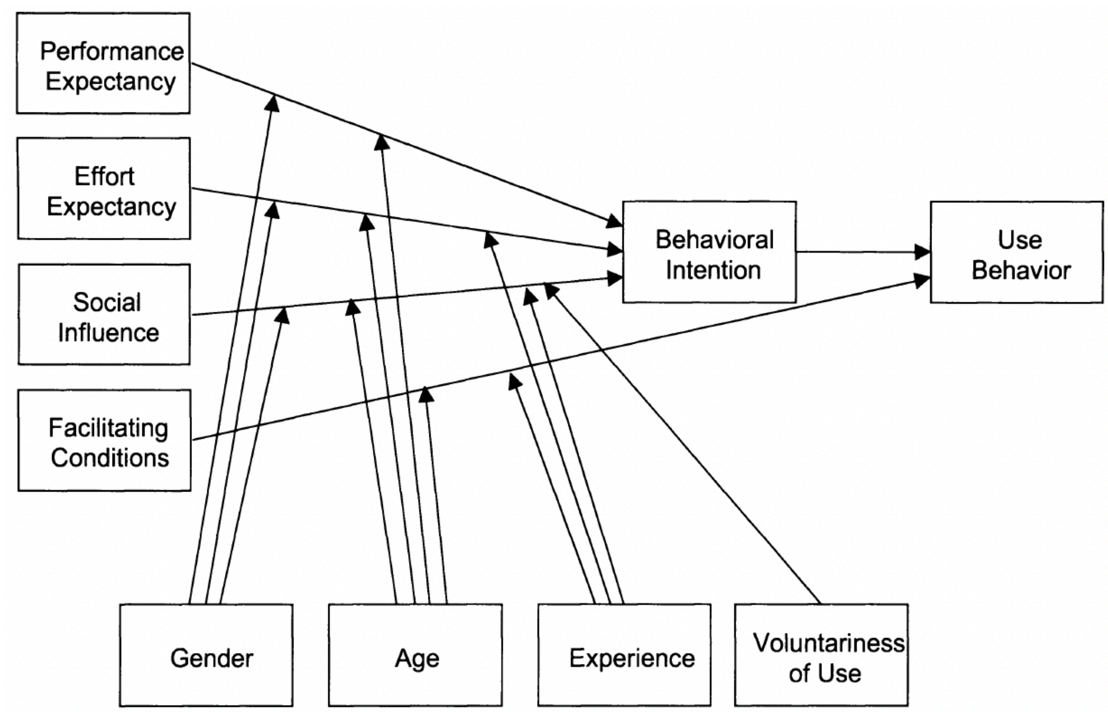

Figure 1: Original UTAUT model (Venkatesh et al., 2003). Adopted from Venkatesh et al. (2003), MIS Quarterly, 27(3), p. 447

UTAUT consists of four main constructs that are used to predict the intention to adopt and use technology (Venkatesh et al., 2003; Venkatesh et al., 2012). Performance expectancy is the level or degree to which an individual believes using a system will lead to gains in their job performance (Venkatesh et al., 2003). Performance expectancy originates from five constructs each from a different model in the group of the 8 models that formulated UTAUT (Venkatesh et al., 2003). These constructs are perceived usefulness from TAM and C-TAM-TPB, extrinsic motivation, which was adopted from MM, job-fit, which was adopted from MPCU, relative advantage which was adopted from IDT, and outcome expectations which was adopted from

SCT (Venkatesh et al., 2003). These constructs are said to have been the most significant when measured separately within their respective models and performance expectancy was also observed as the most significant variable in UTAUT (Venkatesh et al., 2003). The second construct, effort expectancy, is defined as the degree of ease associated with the use of a system (Venkatesh et al., 2024; Venkatesh et al., 2003). Effort expectancy as developed from 3 constructs drawn from 5 of the synthesized models, namely: perceived ease of use from TAM, complexity adopted from IDT, and effort perception from MPCU, MM, SCT (Venkatesh et al., 2003). Third, Social influence is also a major construct within the UTAUT framework exhibiting a significant relationship with behavioral intention in the adoption of technology (Venkatesh et al., 2003, Venkatesh et al., 2012). Social influence was also drawn from 3 constructs, namely: subjective norm adopted from TRA, TPB and C-TAM-TPB, social factors adopted from MPCU, and Image adopted from IDT (Venkatesh et al., 2003). And fourth, facilitating conditions is a major construct within the UTAUT framework (Venkatesh et al.,2003). It measures what the organization provides as resources and support for the employee when a new technology is being implemented. As such, the management team should be a reliable source of information for employees during the process of technology adoption. Facilitating conditions was drawn from: perceived behavioral control adopted from TPB and C-TAM-TPB, facilitating conditions adopted from MPCU, and compatibility adopted from IDT (Venkatesh et al., 2003). While all the four main constructs of UTAUT are worthy of additional research, this study focused on social influence because it captures the normative voice most directly relevant in understanding how employees respond to AI-related risks in organizational settings.

UTAUT is one of the most effective models used in the study of technology adoption (Gerlich, 2023; Martins et al., 2014). The model was developed to provide managerial teams and scholars a tool that could be used to examine the probability of successfully adopting a technology (Venkatesh et al., 2003). UTAUT consistently demonstrates strong predictive validity explaining a significant proportion of variance in the intention to adopt technology (William et al., 2019; Lai, 2017; Venkatesh et al., 2012; Venkatesh et al., 2024; Dwivedi et al., 2019). In the original study conducted by Venkatesh et al., (2003), UTAUT outperformed its predecessors by explaining 65% - 70% of the variance in intention to adopt while the original eight individual models explained between 17% and 53%. UTAUT has been used to test technology adoption in various fields including healthcare information systems (Venkatesh et al., 2016), tax systems (Venkatesh et al., 2016) internet banking (Martins et al., 2014), AI adoption (Venkatesh et al., 2024), Mobile Technologies (Venkatesh et al., 2016) amongst other areas of technology.

Behavioral Intention

In the study of technology adoption, behavioral intention (BI) is a key construct and used as an antecedent to actual usage behavior (Ajzen, 1991; Venkatesh et al., 2003). It is defined as an individual's motivational readiness or deliberate plan to perform a specific behavior (Ajzen & Fishbein, 1975; Kulviwat et al., 2009; Maruping et al., 2017). Intentions reflect the effort an individual is likely to invest in carrying out the behavior, making them a critical predictor in models assessing technology use (Ajzen, 1991; Eckhardt et al., 2009). Initial theoretical grounding for BI stems from the Theory of Reasoned Action (TRA), which posits that behavior is directly influenced by behavioral intention which is shaped by beliefs and attitudes toward the specific behavior (Ajzen & Fishbein, 1975; Chau & Hu, 2002). TPB, as an extension of TRA, posits that BI is jointly influenced by subjective norms, attitude, and perceived behavioral control (Chau & Hu, 2002; Mathieson, 1991). These foundational theories underscore the idea that behavioral intentions are formed from both personal evaluations, attitudes, and social influences, subjective norms, as well as an individual's subjective confidence in their ability to execute the behavior (Kulviwat et al., 2009; Karahanna et al., 1999).

In the context of information systems research, BI has become one of the most frequently used dependent variables in examining the acceptance and use of new technologies at the individual level (Venkatesh et al., 2003; Maruping et al., 2017). This prominence is reinforced by empirical evidence demonstrating a strong correlation between intention to use and actual system usage (Chau & Hu, 2002). Particularly in survey-based studies, BI is considered a more practical and valid measure than actual usage, especially when adoption is prospective or emerging (Venkatesh et al., 2012). BI plays an essential role in more recent frameworks such as the Unified Theory of Acceptance and Use of Technology (UTAUT), which consolidates prior models to identify performance expectancy, effort expectancy, social influence, and facilitating conditions as predictors of behavioral intention (Venkatesh et al., 2003). Within UTAUT, BI functions as a critical intermediary variable through which these constructs influence actual usage behavior. In their extension of the UTAUT model, Venkatesh et al. (2012) further validated BI's role across a range of technologies with consumers as the target population when they established and empirically tested UTAUT2.

In the realm of artificial intelligence (AI), BI has become especially relevant given the transformative and often disruptive nature of AI as a form of technology. Behavioral intention toward AI reflects an individual's readiness to adopt AI tools in the workplace, shaped by factors such as perceived usefulness, risk, ease of use, and trust (Davis, 1989; Venkatesh et al., 2003; Bankins & Formosa, 2023). Research increasingly shows that employees' intentions to adopt AI are influenced not only by the functional attributes of the technology but also organizational and psychological factors. For instance, Bankins and Formosa (2023) found that organizational trust and confidence in leadership's AI strategy significantly predicted employees' intention to engage with AI systems. Similarly, Lai et al. (2024) and Gerlich (2023) emphasize that perceived risk and cultural attitudes toward automation also moderate BI in AI contexts.

Examining behavioral intention provides a theoretically grounded and empirically supported means to assess individuals' predispositions toward adopting AI, especially in organizational environments where actual usage may be influenced by institutional mandates, readiness, and trust in leadership. As such, BI is well-suited as the dependent variable in studies investigating the psychological and organizational factors shaping AI adoption.

Perceived Risk

The Unified Theory of Acceptance and Use of Technology (UTAUT) provides a validated framework in the research of technology adoption. Through its well-known constructs of Performance Expectancy, Social Influence, Effort Expectancy, and Facilitating Conditions (Venkatesh et al., 2003), the model, in its original conceptualization, does not explicitly account for the role of Risk Perception in shaping peoples' behavioral intention to adopt technology. However, understanding how these perceptions of risk influence the decisions associated with AI adoption is critical, given the negative consequences that risk related anxiety can have on employees' acceptance and effective utilization of AI in organizational settings. Employees often confront a complex landscape of perceived risks involving fears that the technology will malfunction or provide inaccurate data. In specialized fields like medicine, clinicians may perceive significant risks such as being misled by inaccurate automated diagnostic tools, yet their intention to adopt may remain high if the technology provides relief from existing heavy workloads (Zhai et al., 2021). Employees also fear job displacement as technology takes over (Zhai et al., 2021), and the potential for confidential data loss as a facet of privacy/security risk present a salient barrier for adoption of the technology (Hassan et al., 2021; Wu et al., 2022). Recognizing and addressing Perceived Risk is important for both scholars and practitioners to help understand and mitigate adoption resistance, reduced productivity and loss of strategic advantages. Specifically, in the adoption of Artificial Intelligence, Perceived Risk has emerged as a significant barrier of users' intention to use the technology (Bankins & Formosa, 2023; P. Kumar et al., 2023; Lebovitz et al., 2022; Laukkanen, 2016). Empirical evidence indicates that perceived risk functions as an inhibitor, primarily through performance risk, the fear of technological malfunction, and privacy risk, concerning the non-consented use of personal data (Featherman & Pavlou, 2003; Martins et al., 2014). Existing literature further suggests that while trust can increase adoption as it reduces uncertainty, higher level of technology fear inhibits behavioral intent of adoption (Cabrera-Sanchez et al., 2021)

Given the complexities surrounding AI adoption, such as, data privacy and security, the fear of losing confidential data (Sharma et al., 2023; Richardson et al., 2021), opacity where employees lack insights on the internal processing of the AI models (Bankins & Formosa, 2023), bias, the systemic inequality derived from biased datasets used in training AI models (Dai & Tayur, 2022; Jussupow et al., 2021), and potential for job displacement (P. Kumar et al., 2023), studying the influence of perceived risk on employees' intention to adopt technology is of vital importance and timely in this era of rapidly emerging technologies. Existing scholarly literature suggests, Perceived Risk, the feeling or perception of uncertainty or potential negative consequences when one is deciding or planning to do something (Featherman & Pavlou, 2003; Shi et al., 2021; Hsu & Lee, 2023; Dowling & Staelin, 1994), could notably influence technology adoption (Nagy et al., 2024). The study of Perceived Risk draws its original roots from consumer behavior and decision-making research, originally developed by Bauer (1960), who defined perceived risk as an individual's perceived uncertainty associated with a particular behavior. Several other scholars extended Bauer's seminal work expanding the definition of perceived risk by reflecting on the respective focused domains of study. For example, several scholars defined perceived risk as an individual's assessment of how risky a situation appears, based on the degree of control they believe they possess, and the perceived level of uncertainty involved (Sitkin & Weingart, 1995; Choi & Ji, 2015; Sitkin & Pablo 1992; Krieger et al., 2024). Other scholars, in their definition, emphasized the anticipation of potential loss or expected negative outcomes associated with an upcoming event (Choi & Ji, 2015; Featherman & Pavlou, 2003; Lai et al., 2024). In his conceptualization of the perceived risk theory, Bauer (1967), associated Perceived Risk as the negative prediction of an outcome of a behavior before the implementation of the behavior. Goh et al. (2024) also defined perceived risk as the individual's subjective assessment or understanding of potential uncertainties associated with a particular situation or activity. Taken together, Perceived Risk alludes to uncertainty and a negative anticipation towards a potential outcome of a behavior or activity prior to engaging in the behavior or activity. The individual's inability to predict the consequences of an action or behavior, or the unfavorable results ultimately manifests as the individual's perception of risk towards that action or behavior. High levels of perceived risk often prompt individuals to engage in protective behaviors that outweigh their willingness to adopt new technologies (Schwesig, 2023). In addition, perceptions of risk are not formed in isolation but are shaped by individuals' previous experiences and prior behaviors, which influence how they evaluate new situations (Schwesig, 2023).

Featherman & Pavlou (2003) advanced the study of Perceived Risk by identifying and validating seven distinct dimensions which collectively form a second order construct and are commonly used as the composite measure of perceived risk (Featherman & Pavlou, 2003; Martins et al., 2014). Analyzing these dimensions individually has allowed researchers to identify which specific aspects of risk are most salient in different adoption contexts (Featherman & Pavlou, 2003). Based on Featherman & Pavlou (2003) the seven dimensions of risk are: (i) performance risk, the likelihood that the AI technology will malfunction, fail to meet expectations, or underperform, resulting in the inability to deliver the intended benefits, (ii) financial risk, the potential financial consequences associated with AI adoption, including costs related to initial implementation, ongoing operations, and potential losses from security breaches or fraudulent AI activities; (iii) time risk, the possibility that employees will waste time researching, learning, and integrating AI systems, only to later replace or revise them due to performance deficiencies or unmet expectations; (iv) psychological risk, the potential for AI adoption to negatively impact an individual's psychological comfort, self-perception, or self-esteem, particularly when adoption efforts result in frustration or failure; (v) social risk, the risk of reputational harm or diminished status within one's professional or social group if AI adoption is perceived as ineffective, unreliable, or misaligned with organizational expectations; (vi) privacy risk, the threat of losing control over personal or organizational data during AI adoption, including risks related to unauthorized data use, breaches of confidentiality, or identity theft for fraudulent purposes; and (vii) overall risk, holistic evaluation of perceived risk, reflecting the combined assessment of all individual dimensions associated with AI adoption.

As the popularity and use of AI increases in organizations, for example, in the infusion into commonly utilized workflows and simple tasks, the fears and feelings of uncertainty are exacerbated amongst employees (Schwesig, 2023, Gerlich, 2023). Perceived Risk as a barrier to technology adoption often leads to fear among individuals, employees, and can manifest through various responses including feelings of uncertainty, discomfort, anxiety, internal conflict, concern, psychological unease, emotional distress, or cognitive dissonance (Featherman & Pavlou, 2003). Perceived risk may result from intangibility of technology systems, the usability, the vendor of the product, lack of trust and familiarity of the technology, or absence of a relationship with the vendor or creator of the technology (Yang et al., 2015). Opacity, defined as the difficulty to understand the reasoning behind a given outcome when such a reasoning is obscured or hidden from view (Lebovitz et al., 2022), has been identified as a major barrier or inhibitor of AI adoption. In the medical industry for example, the lack of transparency is a major inhibitor for physicians and patients to establish trust with AI systems (Kyung & Kwon, 2022). Research on AI adoption amongst physicians and clinicians, who can be held liable and damage their reputation in case of errors (Dai & Tayur, 2022), indicates they are reluctant to accept results generated by systems that lack transparency (Bankins & Formosa, 2023) which leads to avoidance or rejection of AI systems in the medical industry (Lebovitz et al., 2022). The black-box nature of many AI systems means the end-users and even AI developers cannot understand how an AI generates its outputs (Bankins & Formosa, 2023). Physicians perceive it as high risk for their careers and the patients' well-being to blindly accept the results derived from an opaque or black-box system model (Buomsoo et al., 2023). Automation strategies are likely to exacerbate employees fears of being displaced or losing their jobs to the AI systems implemented (P. Kumar et al., 2023; Raisch & Krakowski, 2021). While desire to improve efficiency and reduce costs makes automation-based AI systems attractive, research indicates that profits decline when employees are laid off after an automation-based AI system implementation (A. Kumar et al. (2023).

AI systems require large amounts of data for model training in the quest for perfection. The acquisition of this data raises serious concerns about privacy, consent, and surveillance (Bankins & Formosa, 2023). There appears no clear explanation where the data is retrieved from and what type of data is ingested into the machine learning models (Samorani et al. 2022). This has led some to highlight the concern that the use of private information for AI predictive models may not be legal and may be an invasion of privacy (Samorani et al. 2022) leading to increase of fears related to the AI systems. Management and AI developers must consider customers' and employees' needs, desires and attitudes during the design, implementation, and use of the AI systems to alleviate fears that decrease the intention to adopt AI (Richardson et al., 2021).

Organizations operating in highly regulated industries must adhere to complex legal and regulatory frameworks that require higher levels of accountability in their operations and business conduct. Drawing from prior technology adoption literature in the medical industry as an example, it is not clear who would assume the liability in the event AI systems make mistakes. Would it be the health experts, the management, or the systems developers (Dai & Tayur, 2022)? Fears emanating from the ambiguity, lack of accountability, and potential liability associated with the use of AI, has led some physicians to limit their use of the technology to cases where AI tends to confirm, rather than contradict the physicians' diagnoses taking away the vast advantages associated with using the system in augmentation (Dai & Tayur, 2022).

Perceived Risk continues to play a critical role in shaping the behavioral intention of AI adoption. Multiple empirical studies have established a generally negative correlation between PR and BI, where increased perceptions of risk correlate with reduced willingness to adopt AI technologies (Nagy et al., 2024; Lai et al., 2024). However, emerging scholarship suggests that this relationship may be contextually moderated. Schwesig (2023), for example, contends that

Perceived Risk does not uniformly deter adoption, proposing instead that individual, organizational, and contextual variables may condition how PR influences behavior.

Social Influence

Despite the substantial benefits that AI offers to organizations, many employees are still uncertain and have doubts about the technology. While the studies of Perceived Risk towards AI adoption offers some responses towards combating this skepticism, it's also clear that other influential factors like social dynamics within the workplace (Venkatesh et al., 2003, Venkatesh et al., 2012) also play a significant role in shaping the employees' behavior and intention to adopt AI. Perceived risk may emanate from a lack of experience or familiarity with the technology. When an individual perceives risk towards a particular subject, they are naturally inclined to familiarize themselves about the subject, becoming more knowledgeable (Dowling & Staelin, 1994). In the absence of knowledge, they could also turn to people they trust or are familiar with for information (Siegrist et al., 2005). They could look for information from those they consider close or important to them, hence they could be influenced by their social networks. People consider the opinions of family and friends (Gerlich, 2023) and cultural norms (Figueroa-Armijos et al., 2023) as sources of valuable information when they are making decisions. Understanding these social influences by individuals not only provides insights into overcoming technology rejection caused by Perceived Risk but also offers guidance for facilitating effective technology integration and utilization by organizations.

Social influence (SI), also known as peer group pressure, has previously been defined as an individual's perception of the opinion of others important to the individual (Eckhardt et al., 2009). Social influence reflects the extent to which individuals perceive that important others believe they should engage in a particular behavior or adopt a technology (Venkatesh et al., 2003). It's not only the opinion of the other people, but Social Influence can also be in the form of their recommendations and behaviors (Eckhardt et al., 2009; Maruping et al., 2017). According to Kelman (1958), SI manifests itself through three distinct psychological processes: compliance, identification and internalization, each reflecting a different pattern of internal cognitive and emotional engagement. These processes and social mechanisms shape the perception and lead individuals to formulate opinions about technology aspects and how their important other people perceive the usefulness of using the technology (Venkatesh & Bala, 2008). As such, SI also reflects broader factors, including opinions and behaviors of important others, peers, friends, and relatives, which can significantly impact an individual's intent to adopt technology (Martins et al., 2014; Maruping et al., 2017).

Compliance as a process of SI, involves a change in behavior largely driven by external pressures exerted by important others with the hope of achieving favorable responses, gains, or avoid punishment imposed by influential people or authority figures (Kelman, 1958; Venkatesh & David, 2000). In other words, the individual conforms and adheres to the expectations of others (Eckhardt et al., 2009). The behavior being adopted may not necessarily be aligned with the individual personal beliefs, but they adopt it to conform to the social expectations with the intent to gain approval or avoid negative consequences (Venkatesh & David, 2000). The compliance process is closely aligned to subjective norms which refers to an individual's perception of social expectations held by important others, together with their personal motivation to comply with certain expectations (Eckhardt et al., 2009; Venkatesh & Bala, 2008). Subjective norms are generated by normative beliefs, what an individual believes important others think they should be doing or behave, and the corresponding pressure to act accordingly (Karahanna et al 1999; Kulviwat et al., 2009; Chau & Hu, 2002). Normative influence, in line with compliance, entails the belief that certain behaviors are expected or discouraged by people or groups the individual considers significant (Kulviwat et al., 2009), inducing normative pressures that often shape intentions and behaviors, as individuals tend to conform to the standards of their social groups (Kulviwat et al., 2009). As individuals observe behaviors of their peers and compare themselves, they are inclined to conform to avoid standing out (Eckhardt et al., 2009). People learn, emulate, and adopt behaviors based on what they see in their social groupings (Yi et al., 2006).

According to Kelman (1958), identification, the second process of influence, occurs when individuals adopt behaviors and attitudes to align themselves with a person or group they admire or feel connected with to identify with the person or group. Identification is triggered when the individual forms a connection with a likable or influential source and the resulting behavior and feeling may remain only when the likeable source is present (Karahanna et al., 1999). The content of the behavior being adopted may not be the primary objective, even though they might believe in the behavior, it maybe the act of conforming itself, which brings social or psychological satisfaction that drives the process of identification (Kelman, 1958). In organizational settings, concerns over professional image and status may drive individuals to align their behavior with that of influential referents (Yi et al., 2006; Karahanna et al., 1999; Venkatesh & Bala, 2008). Identification as a process of SI reflects an individual's motivation to align with important others, to preserve or elevate their social image, and establish a sense of belonging. Venkatesh & Bala (2008) refer to image as the extent to which the individual perceives their use of a technology will enhance their status in their social group. Considering individuals are concerned about the image they present at the workplace (Yi et al., 2006), social influences, through the process of identification, may trigger individuals to act in a certain way to preserve or acquire a perceived image (Yi et al., 2006).

Kelman's (1958) third process of influence, internalization occurs when the individual accepts influence as a result of perceiving the content of the behavior observed or the belief is congruent with their own value system and is intrinsically rewarding to them. Internalization happens especially when the advocated behavior is endorsed by credible experts (Karahanna et al., 1999; Maruping et al., 2017). Individuals are also likely to adopt behaviors that present an intrinsic interest, the joy attained when performing a specific behavior (Maruping et al., 2017). Individuals are more likely to internalize the use of technology when they perceive it be more genuinely useful, not only because others recommended it but also, importantly, they recognize its value based on their own assessment and needs (Yi et al., 2006). The concept of incentive alignment, which correlates and aligns with internalization, refers to the degree to which the perceived benefits of a system or technology are aligned with an individual's or group's expectations and values (Venkatesh & Bala, 2008). Systems must offer incentives to the user that they can relate with as a benefit to them, if not, they will not internalize or accept the system if other factors are not considered.

Social Influence manifests through these three qualitatively distinct yet interrelated processes, i) compliance, when behavior is shaped by external pressures and the desire for approval or sanction avoidance, ii) identification, where the individual is motivated to align with important others to preserve or elevate their image, and iii) internalization, when the adopted behavior aligns with the individual's intrinsic values and is rewarding (Kelman, 1958). Closely related to these processes are the constructs of subjective norm, the perceived expectations of important others (Eckhardt et al., 2009; Venkatesh & Bala, 2008) and image, the belief that adopting a specific behavior for example, use of technology, would enhance one's status or reputation in a social group (Yi et al., 2006; Karahanna et al., 1999). Combined, these concepts provide a useful framework to understand how social dynamics influence individuals' intention to adopt technology including AI where peer pressure from colleagues, supervisors, perceived value to be gained and personal images at the workplace are all sources of influence. Social Influence is regarded as a major determinant of technology adoption due to its role in shaping internal beliefs and perceived social expectations (Gerlich, 2023; Maruping et al., 2017). Social Influence may arise from direct pressure, such as encouragement from supervisors and colleagues, or indirectly, through observations of peers and secondhand perceptions of leadership behaviors (Figueroa-Armijos et al., 2023; Kramer, 1999). For example, individuals may adopt or reject AI technologies based on how those in their social networks express support, skepticism, or indifference toward the technology (Yi et al., 2006).

In technology adoption research, social influence is frequently conceptualized as subjective norm, for example, in the Theory of Planned Behavior (Ajzen, 1991), and has been extensively operationalized in studies using Venkatesh et al. (2003) Unified Theory of Acceptance and Use of Technology, UTAUT (Eckhardt et al., 2009). These models emphasize that individuals often align their actions with group norms to maintain social cohesion and avoid appearing different (Eckhardt et al., 2009). The concept of image plays a vital role in reinforcing identification, as individuals assess whether adopting a technology will elevate or diminish their perceived status within professional or peer groups (Karahanna et al., 1999). Although the influence of social influence on technology adoption has been widely studied, empirical results remain mixed. Some scholars report significant relationships between social influence and behavioral intention to adopt new technologies (Venkatesh et al., 2003; Kulviwat et al., 2009), while others have found limited or no significant effects (Davies et al., 1989; Figueroa-Armijos et al., 2023). Even though during the development of TAM (Davies et al., 1989) the team found SI was not a significant influencer of BI and chose to eliminate it from the model. Venkatesh et al., (2003) found that social influence was significant in influencing BI especially in environments where the individual was required to adopt the technology, hence the inclusion of voluntarism as a moderating element in the relationship between SI and BI. Further insights from existing literature suggest that non-adopters may be more susceptible to peer influence than adopters (Eckhardt et al., 2009), highlighting the importance of understanding the full spectrum of SI in the technology adoption decision. Venkatesh et al., (2003) found that women, particularly older women were also more susceptible to influence especially in mandatory settings that required adoption of new technologies while younger users of technology were driven more by extrinsic rewards. Individuals in an organization may choose, due to pressure, to conform some individuals may choose to adopt a behavior if important others say or indicate that they should adopt the behavior, hence the opinion of others to use or reject technology could mold the opinion and feelings of an individual towards their opinion of the technology (Yi et al., 2006). Pressure from supervisors may also lead to technology acceptance (Figueroa-Armijos et al., 2023). Secondhand information about leaders in the organization could influence opinions and actions (Kramer, 1999) of employees to act against the wishes or plans of the organization.

Organizational Trust

As organizations increasingly adopt AI in the hope of spurring growth, increasing efficiency and gaining market advantages, understanding the factors that influence employee BI continues to be a focal point of academic inquiry. Extant research has focused on key predictors such as perceived usefulness, effort expectancy, and social influence, the core constructs in

UTAUT (Venkatesh et al., 2003). Additional studies since the original UTAUT was formulated have continued to expand the framework including other variables like perceived risk which has emerged as a major psychological barrier to technology adoption, eliciting fear, uncertainty and resistance (Featherman & Pavlou, 2003; Bauer, 1960; Hsu & Lee, 2023). Upon encountering Perceived Risk, individuals' natural response is to seek out knowledge (Dowling & Staelin, 1994) about the subject or behavior from multiple sources, including peers and organization leadership teams. They seek information from people they perceive as credible or people they trust (Siegrist et al., 2005). Trust relates to the confidence one perceives from another party based on their actions, words and decisions (Liu et al., 2025). This confidence can be in relation to an individual or to an organization (Mayer et al., 1995). Organization Trust is a pivotal element in the effective functioning and long-term success of any organization with a higher level of trust between the employees and the organization enhancing collective team performance (Liu et al., 2025). Cultivating and sustaining trust should be viewed not merely as a cultural asset, but as a strategic imperative central to organizational resilience and performance (Mayer et al., 1995; Shockley-Zalabak et al., 2000).

Trust has long been perceived as the willingness to take a risk and the amount of risk one is willing to take correlated to the level of trust, they are willing to give (Schoorman et al., 2007). The propensity to trust, a human's predisposition to trust others or generally expect others to be trustworthy (Mayers et al., 1995), alludes to trust being highly based on relationships (Schoorman et al., 2007). Recognizing that trust involves individual willingness to accept risk and is influenced by relational dynamics, it becomes important to explore how this general concept of trust translates into the context of organizations. Although numerous definitions of organization trust have been documented in existing literature, a consensus on a precise definition has not emerged, with some definitions placing emphasis specifically on ethical dimensions and others on social dimensions (Kramer 1999). In some studies, Organizational Trust has been defined as the willingness of employees to be vulnerable based on positive expectations of the organization with regards to its intentions, motives and conduct (Liu et al., 2025; Mayer et al., 1995). Shockley-Zalaback et al., (2000) described organizational trust as the individuals' favorable assumption about the intentions and behaviors of various members of the organization based on their roles, relationships, shared experiences and inter-dependencies. They further noted that trust in the organization was reflected by how individuals perceived the ability to form new networks and associations to accomplish business tasks (Shockley-Zalaback et al., 2000). Despite the scholarly divergence in definitions, Kramer (1999), in his literature analysis, concluded that trust was essentially a psychological state that is based on multiple aspects of cognitive processes and orientations suggesting that trust, including in organizational settings, may best be examined and viewed on attributes based on a specific context, the trustor and trustee (Kramer, 1999). Like individuals, organizations differ in the extent to which they are trusted by their employees (Schoorman et al., 2007), additionally, within the same organization, employees' perceptions of organizational trust may vary based on the nature and quality of their relationships with management and differentiate and assign varying levels of trust towards the management teams and organization as a whole (Liu eta l., 2025).

Several factors within the organization contribute to organization trust. Employees develop trust in their organizations through an evaluation of several organizational factors, including top management, human resource practices, organization culture, and governance structures in place (Lie et al., 2025). These aspects contribute to the employees' perception of the organization's intentions and trustworthiness. Formal structures like organizational rules serve as a foundational component in trust development (Mayer et al., 1995; Kramer, 1999). The use of rules and legalistic remedies is used in some organizations as a mechanism for the organization to protect its interests because of low levels of organizational trust (Mayer & Davis, 1999). Aspects institutionalized at the macro level, through governance structures, policies and expected norms by management, translate to the micro-level i.e. the internalization of trust by the individual employees (Kramer, 1999). Trust based on rules in an organization, is predicated by an understanding by all involved of the system of rules that determine appropriate behavior and conduct (Kramer, 1999). However, excessive organizational controls may impede trust formation, as actions by the trustee might be seen as responses to enforcement rather than authentic indicators of trustworthiness (Mayer et al., 1995). When actions by the organization leadership team appear to be driven primarily by compliance rather than discretionary choice, trustors may question the sincerity or integrity of those actions (Mayer et al., 1995). Kramer (1999) further argues that rules-based trust within organizations depends on shared understanding or behavioral expectations and appropriate conduct. In come case, organizations must rely on legalistic remedies or extensive rule enforcement as a compensatory mechanism when there is a low level of trust in the organization (Kramer, 1999), to enforce controls. The human predisposition to trust draws from their past experiences and particular experiences related to trust with individuals they encountered in their past (Kramer 1999). This trust, based on past experiences, which is predicated upon information from others acts as secondhand information, and suggests that repeated actions, whether positive or negative, influence the development of trust, reinforcing or eroding it between the trustees and trustors in the organization (Kramer, 1999).

Employees engage in collaborative behaviors as they develop trust in their organization. They also form alliances and develop cross-functional networks that support the execution of strategic goals and maintain operational viability (Shockley-Zalabak et al., 2000). Trust fosters an environment where individuals feel confident in one another's intentions, which in turn increases their willingness to take interpersonal risks and contribute meaningfully to collective efforts (Mayer et al., 1995). Other positive outcomes documented in the extant Organizational Trust literature include but are not limited to increased individual and team performance (Liu et al., 2025; Mayer et al., 1995), better cohesion within the workforce (Liu et al., 2025; Shockley-Zalabak et al., 2000; Kramer, 1999), improved communication across all levels of the organization (Liu et al., 2025;), better knowledge sharing (Liu et al., 2025;), goal setting (Shockley-Zalabak et al., 2000;), and effective crisis management (Shockley-Zalabak et al., 2000). Additionally, as members of an organization identify with the organization, they are proud to be associated with the brand and carry it with pride which leads to the organization brand benefiting as its ambassadors carry its flag wherever they go (Shockley-Zalabak et al., 2000). Achieving shared organizational goals in complex environments requires a foundation of mutual trust that enables individuals to collaborate effectively and assume collective responsibility for outcomes (Mayer et al., 1995). Without such a foundation, organizations risk inefficiencies, fractured communication, and diminished morale.

The study of organizational trust is grounded in multiple theoretical frameworks drawn from psychology, sociology, and organizational behavior, each offering valuable perspectives on how trust emerges, evolves, or deteriorates within institutional contexts (Kramer, 1999). Within the organizational behavior tradition, trust is commonly conceptualized as a relational construct shaped by leadership behavior, communication processes, organizational culture, and perceptions of procedural and distributive fairness. These factors influence how individuals assess others' intentions and reliability, ultimately shaping their willingness to accept vulnerability in workplace relationships (Kramer, 1999; Mayer, Davis, & Schoorman, 1995). Several theories have been used in the study of OT, among them, the Rational Choice Theory contributes an economic and decision-theoretic lens, positing that trust is a rational calculation wherein individuals assess the expected benefits and potential risks of trusting another entity or engaging in a particular course of action (Kramer, 1999). In organizational settings, this perspective implies that employees are more likely to trust leadership or adopt new systems, like AI technologies, when they perceive that the anticipated gains outweigh the possible losses or uncertainties involved. Social Exchange Theory (SET) offers another important perspective, emphasizing that trust develops through reciprocal, interdependent exchanges over time (Blau, 1964; Cropanzano & Mitchell, 2005). According to SET, trust arises when individuals perceive that positive treatment received from others, the management team or organization, will be reciprocated. In organizational contexts, this reciprocal dynamic enhances commitment, engagement, and openness to innovation. Trust thus becomes a medium of exchange that supports team effectiveness, knowledge sharing, and acceptance of change, including the adoption of new technologies (Cropanzano & Mitchell, 2005; Fulmer & Gelfand, 2012; Liu & Tekleab, 2025). One of the widely known frameworks in the study of Organization trust is the Integrative Model of Organizational Trust developed by Mayer et al. (1995), which conceptualizes trust as a willingness to accept vulnerability based on the belief that another party will act in ways that are important and beneficial to the trustor. This model identifies three core dimensions of perceived trustworthiness i) ability, ii) benevolence, and iii) integrity and posits that trust is also moderated by the trustor's general propensity to trust and perceptions of situational risk. The model's multidimensionality allows it to be applied across individual, dyadic, team, and organizational levels (Mayer et al., 1995; Schoorman, Mayer, & Davis, 2007). The Integrative Model of Organizational Trust is considered a robust model and is well trusted and used for the analysis of organization trust research (Schoorman et al., 2017).

Ability, also referred to as competence (Shockley-Zalabak et al., 2000), is the perception that the organizational leadership can steer the organization and perform well to survive in the existing competitive landscape (Shockley-Zalabak et al., 2000; Mayer & Davis, 1999) It carries an expectation that the management team has the required expertise to run the organization (Shockley-Zalabak et al., 2000). Ability is a set of skills and competencies that increases influence of an organization within its domain (Mayer et al., 1995). The leader's role within an organization signifies their capabilities and abilities and if viewed based on a specific context, may influence the level of trust towards the leader and reduce or increase the burden of negotiating trust when engaging with others (Kramer, 1999). By accepting elements of work roles, employees express trust towards their managers abilities (Costigan et al., 1998).

Integrity refers to the adherence to an acceptable set of values or principles the trustor deems important like honesty, fairness, and consistency (Mayer & Davis, 1999). As employees perceive the organization leadership team to be open and sincere, they accord more trust to them and to the organization. (Shockley-Zalabak et al., 2000). Perceived level of integrity outweighs the reasons why the perception was formed (Mayer et al., 1995). This factor of trust carries an assumption that the trustee poses values that are considered positive by the trustor (Mayer & Davis, 1999). The employee's perception that the management team confirms to principles that the employee deems acceptable (Mayer et al., 1995). Integrity perception is shaped by the trustee's past behavior, consistency between words and actions, demonstrations of fairness, and reputational feedback from others (Mayer et al., 1995). The trustor's observation of what the trustee does, how they do it, what they say and if they do as they say, collectively impacts their perception of the trustee's integrity, a critical dimension in the development of trust.

Benevolence according to Schoorman et al., (2007) is defined as, without expecting to profit, the extent of doing good to another person or party. It can be thought of us as showing care and concern to the other party, without the intention of taking advantage especially when the other party appears to be or is in a vulnerable position (Shockley-Zalabak et al., 2000; Mayer et al., 1995). When an employee views the manager as one who cares for their interests, they perceive the manager to possess benevolence (Mayer & Davis, 1999). A trustor's perception of a trustee's positive orientation towards them constitutes benevolence (Mayer et al., 1995). Altruism as a contributor to trust (Mayer et al., 995) signals the trustees intention to act in the trustor's interest, building relational confidence and encouraging reciprocity.

Although ability, integrity and benevolence are discrete independent constructs, each plays a vital role in shaping trust meaning that the absence of any one of the dimensions severely weakens trust levels (Mayer et al., 1995). All three factors contribute to trust such that as perceptions about each of these factors increases, so does the perception of trust (Schoorman et al., 2007). Based on a feedback loop system, the trustor reevaluates the trustee based on incidents and interactions which may cause trust to increase or to decrease (Mayer & Davis, 1999). A manager's ability to appear trustworthy is reflected in how others perceive their ability, benevolence and integrity. This directly translates to the extent to which employees will trust their organization (Schoorman et al., 2007).

Organizational Trust can have a profound effect in shaping employees' responses during the introduction or adoption of new technologies in a company. In some cases, the introduction to technology, particularly technologies related to monitoring, surveillance, or oversight by triggering a feeling of big brother watching over them and a perception that management does not trust employees which leads to erosion of organizational trust as employees reciprocate (Kramer, 1999). On the other hand, higher levels of organizational trust could enhance organizational change initiatives since, as employees accord higher levels of trust to their management teams, they are more likely to accept and support changes, including the introduction of new technologies (Costigan et al., 1998), implying that organization change practices are much more effective when employees trust their managers and leaders (i.e., they have higher levels of organizational trust). Levels of trust for specific parties in an organization, the management team as an example, affects important outcomes in an organization (Mayer & Davis, 1999). This could mean that with higher levels of trust, a management team that desires to introduce a technology could assume a higher probability of adoption by the workforce.

The study of organizational trust has been supported by several validated measurement instruments, including the one that is used in this study based on the Integrative Model of Organization Trust that was developed by Mayer, Davis, and Schoorman (1995). This model defines trustworthiness as being comprised of three key dimensions i) ability, ii) benevolence, and iii) integrity and serves as the foundation for the Trust in Management Scale (Mayer & Davis, 1999), which assesses employees' perceptions of managerial trustworthiness, particularly in contexts involving performance evaluation and organizational change. Another widely used instrument is the Organizational Trust Inventory (OTI) developed by Nyhan and Marlowe (1997), which measures trust in supervisors, coworkers, and the organization itself by focusing on competence, openness, and dependability. Cook and Wall's (1980) Interpersonal Trust Scale has also been frequently applied in studies examining trust between coworkers and within teams, examining faith in others' intentions and confidence in their competence. Shockley-Zalabak et al. (2000) developed the Organizational Trust Index, a multidimensional tool used to assess perceptions of organizational reliability, openness in communication, and concern for employees. Collectively, these instruments offer multiple approaches for measuring organizational trust at various levels and continue to help the advancement of Organization Trust literature.

Hypotheses Development

The significance of Artificial Intelligence (AI) adoption continues to rise due to the technology's potential to enhance organizational efficiency, reduce operational costs, and improve execution speed and accuracy (Arora et al., 2023; Fang et al., 2021; Wang et al., 2023). Despite these advantages, AI adoption introduces trust related risks stemming from data privacy, security, biases, and accountability which create barriers to adoption among potential users (Bankins & Formosa, 2023; Richardson et al., 2021). This dual impact, where benefits coexist alongside significant risks, underscores the need for a deeper understanding of the underlying factors that influence employees' acceptance and adoption intentions towards AI. Behavioral Intention (BI), a central construct within technology acceptance research, is widely recognized as a reliable predictor of actual usage behavior, serving as an essential antecedent to technology adoption (Ajzen, 1991; Venkatesh et al., 2003). By examining BI, researchers and practitioners can better anticipate actual technology use, identify adoption barriers, and strategize effective interventions that enhance successful implementation. To systematically investigate employees' BI toward adopting AI technology, this study employs the Unified Theory of Acceptance and Use of Technology (UTAUT) as its primary theoretical framework. UTAUT has been empirically validated across various technological contexts and consistently demonstrates robust explanatory power, making it one of the most effective and widely applied models for studying technology acceptance behaviors (Gerlich, 2023; Martins et al., 2014). Using UTAUT as the theoretical foundation, the hypotheses that follow are developed to further examine the specific relationships among perceived risk, social influence, organizational trust, and employees' behavioral intention to adopt AI.

According to Schwesig (2023), when individuals consider behaviors with a higher risk likelihood, they are likely to invoke protective behaviors to mitigate the risks. Consequently, if individuals' perceptions towards Artificial Intelligence are associated with risk, the perceptions are likely to impact their intention to use the technology (Gerlich, 2023). Featherman and Pavlou (2003) argue that risk perception is amplified by the perceived importance of the event or technology, indicating that the higher the significance attributed to adopting AI, the higher the employees' inclination toward potential risks, undermining the perceived usefulness of the technology, thereby negatively impacting their behavioral intentions. Conversely, as the employee's risks are reduced or diminished the greater the propensity for them to adopt AI (Martins et al., 2014).

Building on the conceptual foundation established by Featherman & Pavlou (2003), this study conceptualized Perceived Risk as a multidimensional construct consisting of performance risk, financial risk, time risk, privacy risk, psychological risk, social risk, and overall risk. Each of these dimensions impact an individual's decision making and behavioral intentions differently and at varying magnitudes (Featherman & Pavlou, 2003, Martins et al., 2014). In the context of AI adoption in the workplace, where AI systems may exhibit opacity, complexity, bias, privacy issues, these risks are amplified diminishing trust and increasing anxiety and resistance to adoption (Bankins & Formosa, 2023). Accordingly, and based on prior theoretical and empirical insights outlined, this study hypothesizes that higher perceived risk among employees' who regard AI negatively influences their behavioral intention towards the adoption of AI.

H_1: Perceived risk of artificial intelligence negatively associated with their behavioral intention to adopt Artificial Intelligence.

Social Influence has been identified as a significant determinant of individuals' behavioral intention to adopt technology (Venkatesh et al., 2003), especially when the innovation is publicly observable rather than privately consumed (Kulviwat et al., 2009). This observation suggests that the greater the visibility of a behavior within one's social group, the stronger the individual's likelihood to comply with or identify with the group's norms, which, could increase the influence of social factors that influence adoption intentions. In addition, normative beliefs within the workplace, the perception of what one thinks others expect them to do (Kulviwat et al., 2009), may drive the employees' intention to adopt AI, especially when they perceive their managers expect them to utilize the technology. This highlights that adoption decisions are not solely driven by personal attitudes or perceptions of the technology itself but also significantly influenced by social pressures and expectations within the relevant social groups, including places of work (Kulviwat et al., 2009).

Individuals tend to align their behavior with what they believe is expected of them by important others, particularly when those expectations relate to the adoption of new technologies. Subjective norms shape behavioral intention through mechanisms such as compliance with social expectations, alignment of incentives through internalization, and the pursuit of image enhancement through identification with valued social groups (Venkatesh & Bala, 2008). Social comparison further reinforces these dynamics, as individuals choose to conform to established group norms, such as the use of a particular technology within the workplace, to avoid standing out and to strengthen their sense of belonging (Eckhardt et al., 2009). The desire to fit in and maintain group membership can motivate individuals to adopt or use artificial intelligence, even when they harbor concerns about potential risks. This behavior aligns with prior research demonstrating that individuals are often highly attuned to how they are perceived within professional environments leading individuals to engage in behaviors that align with perceived social expectations, particularly when such behaviors serve to maintain or enhance their image (Yi et al., 2006). As such, the potential to improve one's social standing within a group may act as a significant driver of technology adoption decisions. Based on this, this study hypothesizes:

H_2: Social Influence positively influences the behavioral intention to adopt artificial intelligence.

Organization trust influences the employees' decisions and actions in risk-based situations. In the context of AI adoption, some employees may experience uncertainties and have fears about the technology which may increase resistance towards adoption. Considering that the level of trust employees place in specific organizational actors, such as senior management, directly influences critical organizational outcomes (Mayer & Davis, 1999), it is likely that the level of organizational trust could influence their perception of technology, and this may impact their intention to adopt the technology. In the absence of sufficient knowledge, employees may lean on the ability, benevolence and integrity of their leaders to help them bridge the gap of the unknown (Mayer & Davis, 1999; Mayer et al., 1995). As the employee has confidence in the management teams' ability to lead the organization, believe that they have their best interest at heart, and that management has acted with integrity and possesses positive values, the level of organization trust and this will impact the employee's likelihood to adopt a technology that they are not familiar with. In the context of technology adoption also, trust leads to risk taking

(Schoorman et al., 2007; Mayer et al., 1995), a high degree of trust in leadership may increase employees' willingness to embrace new systems. This study hypothesizes that, when management is perceived as competent, benevolent, and acting with integrity, employees are more likely to believe that technology adoption initiatives are being implemented for the collective good, thereby increasing the probability of adoption success.

H_3: Organizational trust is positively associated with the behavioral intention to adopt artificial intelligence.

Employees often adjust their behavior based on the expectations and behaviors of important others, especially in relation to the adoption of new technologies. Social Influence (SI) reflects the extent to which the individuals believe important others believe they should use the new technologies (Venkatesh et al., 2003; Venkatesh et al., 2012). When there is a higher level of social influence, individuals may be inclined to mitigate their own perceptions of uncertainties and fears to conform with the social norm. This may be especially true when important others endorse the use of technology. The Unified Theory of Acceptance and Use of Technology (UTAUT) position SI as a direct determinant of behavioral intention of technology adoption (Venkatesh et al., 2003), in addition, broader social and organizational theories also suggest that the role of SI may extend beyond a direct effect to a moderating effect. From the perspective of Social Influence Theory (Kelman, 1958), individuals move from initial compliance to internalization, where the technology's trust worthiness is validated through the observable success of peers. Similarly, Social Identity Theory (Tajfel & Turner, 1979) posits that individuals acquire part of their self-identity from group membership and are motivated to align their behaviors with norms that associate them with certain groups. In organizations where AI adoption is deemed positive, normative endorsement from influential in-group members can attenuate the effect of perceived risks through their endorse of AI adoption as a valued identity.

Where strong social influence exists, the perceived social cost of non-conformation may outweigh individuals concerns regarding uncertainty and potential negative outcomes. Consequently, the expected negative effect of perceived risk on behavioral intention to adopt AI should be weakened when social influence increases. This suggests a positive interaction effect, as social influence increases, perceived risk on behavioral intention becomes less negative. Accordingly, this study hypothesizes that social influence would moderate the relationship between Perceived Risk and behavioral intention to adopt AI by weakening the negative effect of Perceived Risk on intention to adopt.

H_4: Social Influence moderates the relationship between perceived risk and behavioral intention to adopt artificial intelligence by weakening the negative effect of perceived risk on the behavioral intention to adopt artificial intelligence.

In the absence of sufficient knowledge or familiarity with new technologies, individuals often turn to trusted sources to inform their decisions (Siegrist et al., 2005). Within organizations, employees' trust in the management team serves as a key factor influencing how they interpret and respond to the risks associated with adopting technologies such as artificial intelligence (AI). When individuals have a high trust level on the organization, they are more likely to expect positive outcomes from its actions, even in uncertain circumstances (Shockley-Zalabak et al., 2000). As a result, organizational trust can mitigate the Perceived Risk employees associate with adopting AI. Trust facilitates risk-taking behavior (Mayer et al., 1995; Schoorman et al., 2007), implying that employees who trust their organization are more likely to comply with its initiatives, even when those initiatives involve technologies with which they are unfamiliar. High levels of organizational trust, rooted in perceptions of leadership's ability, benevolence, and integrity, can reduce the psychological barriers associated with risk (Mayer et al., 1995). Thus, employees who perceive their organization as trustworthy may be more willing to overlook uncertainties related to AI, relying on their belief that the organization acts in their best interest and can navigate the risks on their behalf.

Pavlou and Gefen (2004) suggested that perceptions of institutional effectiveness enhance trust, which indirectly shapes how risk is evaluated. Varying levels of trust influence the extent to which employees are willing to accept risk; when trust is high, employees are more inclined to accept the risks associated with adopting AI because they believe in the competence and ethical standards of their leadership, conversely, lower levels of trust may amplify perceptions of risk, thereby reducing intention to adopt.

Trust is fundamentally relational, involving a willingness to be vulnerable based on the expectation that the trusted party will act benevolently and competently (Shockley-Zalabak et al., 2000; Mayer et al., 1995). As trust increases, the Perceived Risk associated with AI adoption are likely to diminish, thereby increasing employees' willingness to adopt the technology. Based on this, I hypothesize that organizational trust moderates the relationship between perceived risk and behavioral intention to adopt AI, such that higher levels of trust will weaken the negative impact of perceived risk on intention.

H_5: Organizational trust moderates the relationship between perceived risk and behavioral intention to adopt artificial intelligence by weakening the negative effect of perceived risk on behavioral intention.

This study proposed a conceptual model to examine additional factors that influence an employee's behavioral intention to adopt AI. This study drew on the foundational work of previous scholars and utilized UTAUT as the grounding theory to investigate how perceived risk, social influence, and organizational trust shape the intention towards AI adoption. As depicted below, the proposed model hypothesized direct relationships between Perceived AI Risks, Social Influence, Organizational Trust, and Behavioral Intention for AI Adoption. It also explores the moderating roles of Social Influence and Organizational Trust in mitigation the negative impact of perceived risk on behavioral intention.

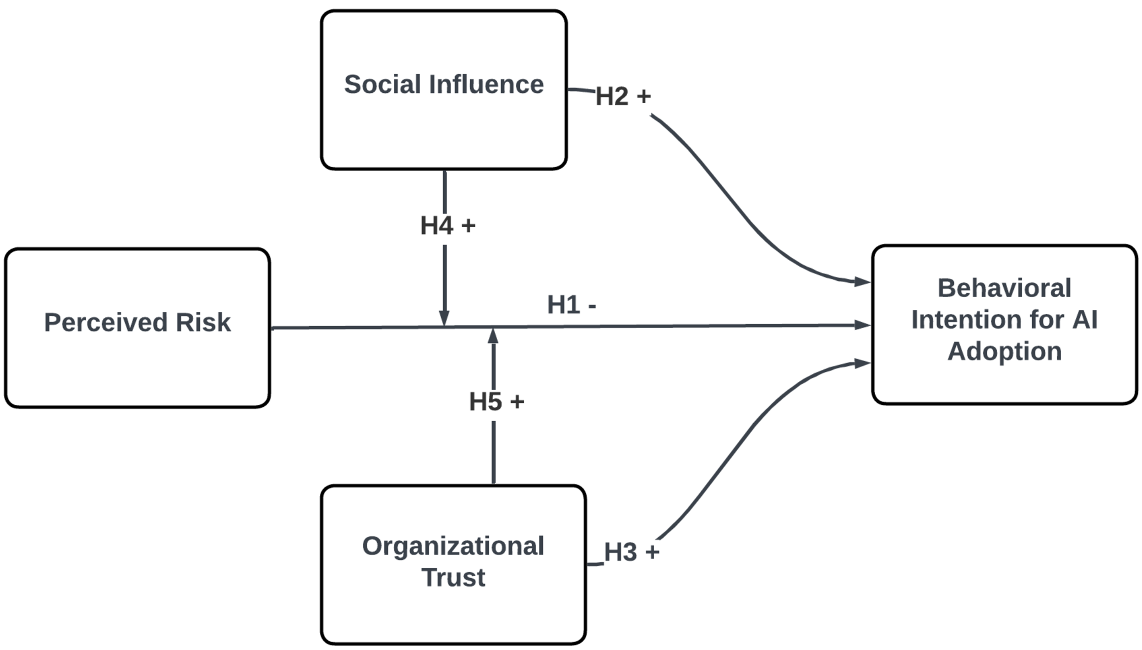

Figure 2: Conceptual Model of the study.

CHAPTER 3: RESEARCH METHODOLOGY

This chapter introduces and outlines the research methodology, data collection approach and the statistical method of analysis used in this study. Quantitative research methodology was adopted for this study to investigate the relationship between perceived risk and behavioral intention to adopt artificial intelligence as well as the moderating effects of social influence and organizational trust. A quantitative research method is well suited for studies seeking to test hypotheses and establish statistical relationships between the variables by analyzing numerical data (Creswell & Creswell, 2017). Accordingly, this study employed structured survey instruments to measure the latent constructs using validated measurement scales, enabling the use of Partial Least Squares Structural Equation Modeling (PLS-SEM) for model evaluation and hypothesis testing. PLS-SEM is suitable for research involving complex models that have numerous constructs, structural paths, and indicator variables without forcing distributional assumptions on the data (Hair et al., 2019). This chapter provides an overview of the research design, including the data collection process, the instruments used, sampling approach and analytical technique. Through rigorous empirical analysis, this study aims to assess the proposed relationships among constructs and determine the extent to which perceived risk, moderated by social influence and organizational trust, influence AI adoption intention behavior in organizational settings.

Survey Approach

A structured online survey was employed to gather empirical data for this study. The survey was designed to capture responses from employees in different job families and positions across a wide range of industries and organizational contexts reflecting the broad applicability of AI use in the current work environments. The survey instrument was administered online via

Qualtrics. The Qualtrics survey included the IRB-approved informed consent language, a consent acknowledgment item, eligibility screening items, and the full set of measurement and demographic questions. Skip logic and display logic were used to implement the screening protocol such that respondents who did not meet the prespecified inclusion criteria were prevented from advancing to the main survey and did not provide substantive study responses.

Participants were recruited using Prolific, an online research participant recruitment platform. On Prolific, potential participants were presented with the IRB-approved recruitment notice describing the study's general purpose and participation expectations, including the requirement to be an adult employed individual residing and working in the United States. Additional eligibility criteria required that participants work for an organization that is currently using AI or plans to adopt AI in the near future, and that participants themselves either currently use AI in their work or expect to use AI in the near future. Eligible participants who accepted the Prolific study invitation were redirected to the Qualtrics survey link to complete the consent process and survey.

The use of an online survey distribution method offers several advantages including accessibility, mobile compatibility, and broader geographic reach, which are all expected to increase the response rates and enhance the diversity of the sample. The participant recruitment company was expected to help recruit survey respondents from a wide geographical area, preferably across all 50 States in the U.S.A, while ensuring viability in demographic characteristics such as age, gender, tenure, and industry.

A brief introduction at the beginning of the survey was used to outline the purpose of the research study, intended use of the data collected, provide informed consent, and assure the respondents of the confidentiality, privacy, and anonymity of their responses. The introduction also emphasized the participation of the survey was entirely voluntary and had been authorized and approved by the University of North Carolina Charlotte's Institutional Review Board (IRB-25-0037) to ensure all data is collected in accordance with the ethical standards for human subject research.

Survey instruments

To examine the relationships among the study constructs, behavioral intention to adopt AI, perceived risk, social influence, and organizational trust, this study administered a structured survey instrument of established and validated multi-item measurement scales. The instrument was adapted and made suitable for measuring the behavioral intention of adapting AI. A standard 7-point Likert scale was used for all the items on the instrument to ensure consistency. Presented as a declarative sentence, a Likert scale item provides response options with varying degrees of agreement or endorsement of the statement (DeVellis, 2016). In comparison to a 5-point Likert scale, the 7-point Likert scale captures greater variation (Hasan et al., 2021) and offers improved reliability, accuracy and ease of use for respondents (Finstad, 2010, Diefenbach 1993). Likert scale is also commonly used in instruments that measure beliefs, opinions and attitudes (DeVellis, 2016). Preston and Colman (2000) found that 5-, 7- and 10-point Likert scales were all perceived as easy to use, and the scales with 7 to 10 categories yielded the highest reliability results. Additionally, this choice aligns with Miller's (1956) findings of human information processing, which suggests that people can effectively distinguish approximately seven categories (plus or minus 2). Combined, these findings suggest that a 7-point Likert scale provides an optimal balance between usability and response precision, with little to no benefit derived from extending the beyond a 7-point scale. Hence, a 7-point Likert scale, ranging from strongly disagree to strongly agree, was selected for this study.

Each of the four constructs in the study (BI, PR, SI and OT) represents a latent variable and cannot be directly observed. This study utilized measures adopted from peer reviewed, established and validated instruments. These instruments were selected based on their reliability and applicability to this study. Below is a description of the measurements for each construct:

1. **Behavioral Intention to Adopt Artificial Intelligence (BI)**

   BI will be measured using a 3-item scale adopted from the Unified Theory of Acceptance and Use of Technology (UTUAT) that was developed by Venkatesh et al. (2003). This instrument has been widely used in various empirical studies (Jewer, 2018; Gansser 2021; Jain et al., 2022; Martins et al., 2014) on technology adoption.

2. **Perceived Risk (PR)**

   PR measurement instruments were adapted from Featherman and Pavlou (2003), which has also been used by Martins et al. (2014) in the study of internet banking services adoption.

   This study did not utilize the social risk facet based on the rationale that Featherman & Pavlou (2003) dropped social risk variable because of its low impact and significance in explaining their model. In addition, this study also dropped the financial risk facet because it's expected the employees in the organization would not be spending a significant amount of money in the procurement of AI technologies, as this should be covered by the organization and therefore not of significance in this study.

3. **Social Influence (SI)**

   SI is the pressure exerted onto a person by important others to take an action, for example, adopt a technology (Martins et al., 2014; Venkatesh et al., 2003; Venkatesh et al., 2012). In our study, we seek to investigate to what extent this influence from important others affects employees in their intention to adopt AI when they have fears or reservations of using the technology. SI's 7-item measurement instrument was adopted from validated scales from Mathieson (1991), Thompson et al. (1991), and Moore and Benbasat (1991).

4. **Organizational Trust (OT)**

   Organizational trust is defined in this study as an employee's willingness to accept vulnerability and take risks based on positive expectations of the leadership team's competence, integrity, and benevolence (Shockley-Zalabak et al., 2000; Liu et al., 2025; Schoorman et al., 2007). To assess this construct, this study employed a validated 17-item measurement instrument adapted from the scale developed by Mayer and Davis (1999). Although measuring trust at an organization level is conceptually distinct compared to the individual level, aggregating the employees' trust perceptions, by linking individual-level assessments to collective trust, to the organizational level is a methodologically accepted practice (Figueroa-Armijos et al., 2023). This approach ensures consistency in the unit of analysis across all study variables.

A complete list of all the items used in the measurement scale can be found in appendix B.

Sampling Frame/Method

This study targeted a population of employed individuals working in organizations across the United States. The study sought to ensure the findings were generalizable as much as possible. Hence, the sampling strategy aimed for diversity across key demographic variables including age, gender, job position/role, career tenure, tenure at the current organization, and industry sector. Participants must have been employed at the time they took the survey in an organization that is using AI technologies or had plans to start using AI soon. Given the research objectives, i.e., studying employed individuals, a non-probability purposive sampling method was employed in this study. The judgmental or purposive sampling technique was selected since its ideal for exploratory studies and due to our specificity and deliberate selection of the sampling inclusion criteria (Taherdoost, 2016).

Sample Size

To ensure the study achieved adequate statistical power, the minimum sample size was determined using multiple criteria. First, the 10-times rule was applied as an initial heuristic check, which recommends a sample size at least ten times the maximum number of structural paths pointing to any endogenous construct or, alternatively, the largest number of formative indicators in a measurement block (Hair et al., 2019). In the present model, the endogenous construct with the largest number of incoming paths was behavioral intention (BI) with 13 predictors; therefore, the 10-times rule suggested a minimum sample size of 130 (10 × 13). Because the 10-times rule is widely regarded as a coarse guideline that can under- or over-estimate required sample size, we also conducted a priori power analysis using G*Power 3.1. Using the "linear multiple regression: fixed model, R^2 deviation from zero" test and specifying a medium effect size ($f^2 = 0.15$), $\alpha = 0.05$, power $(1 - \beta) = 0.80$, and 13 predictors, the minimum required sample size was $n = 118$ (Faul et al., 2009). As an additional robustness check, we considered the inverse square root method proposed by Kock and Hadaya (2018), which provides a more conservative estimate of minimum sample size for PLS-SEM based on the smallest path coefficient expected to be detected. The final usable sample ($n = 297$) exceeded these minimum thresholds, indicating that the study was adequately powered to estimate the proposed model and detect meaningful effects.

Data Analysis

This study utilized Partial Least Squares Structural Equation Modeling (PLS-SEM) as the primary statistical analysis method. PLS-SEM allows researchers to estimate complex models that have numerous constructs, structural paths, and indicator variables without forcing distributional assumptions on the data (Hair et al., 2019). PLS-SEM is appropriate for this study since this analysis method has been widely used for exploratory research where new or not commonly studied relationships are being investigated or during the early stages of investigations (Hasan et al., 2021; Gefen & Straub 2005; Chen et al., 2022). Additionally, PLS-SEM is widely recommended for analyzing intention and belief-based composites (Gefen et la., 2011). With its ability to combine elements of factor analysis by creating composite variables from indicators, PLS-SEM can then use these composites in a path model to test hypotheses about the relationships between constructs (Hair et al., 2019). Given the managerial implications of this research, the ability to generate findings with predictive relevance beyond the study sample is important. The predictive power of PLS-SEM, the ability or capacity of a model in predicting new or unseen data (Hair et al., 2021; Sarstedt et al., 2021), will provide greater utility for future research and management teams based on the findings of this study. Furthermore, PLS-SEM generally provides greater statistical power than covariance-based structural equation modeling, increasing the likelihood of detecting significant relationships (Hair et al., 2019). This implies, the use of PLS-SEM enables robust hypotheses testing while also assessing the practical predictive utility of the proposed research model.

The study followed the confirmatory composite analysis (CCA) procedure (Hair er al., 2020) to assess the results of our reflective measurement model. When assessing and confirming composite measurement models, CCA is the recommended approach for PLS-SEM (Hair et al., 2020). As the first step, we examined the indicator loadings for all the constructs to ensure they meet the minimum recommended threshold of 0.708, which indicates that the construct explains more than 50% of the indicator's variance confirming indicator reliability. The next step involved assessing reliability or internal consistency of the construct by examining the Cronbach's alpha, the exact reliability coefficient, and the composite reliability. If the values lie between 0.70 and 0.95, internal consistency would be established (Hair et al., 2019). Next, we verified convergent validity by ensuring all constructs met the average variance extracted (AVE) threshold of 0.50 and above (Hair et al., 2019). Discriminant validity of the model, an assessment that validates a reflective construct exhibits stronger relationships with its own indicators than with those of another construct in the PLS Model (Hair et al., 2022), was conducted using the Heterotrait-Monotrait ratio of correlations (HTMT) (Henseler, Ringle, & Sarstedt, 2015). The HTMT values were assessed and validated if they met the recommended threshold value of < 0.85. Nomological and predictive validity were checked before the next stage, analysis of the structural model. We used the standard assessment criteria which includes the coefficient of determination (R^2), the blindfolding / predictive relevance based cross validated redundancy measure Q^2, and the statistical significance and reliance of the path coefficients to conduct our structural analysis. Prior to assessing the structural relationships, it is highly recommended to examine collinearity to ensure it does not bias the regression results (Hair et al., 2019). To evaluate collinearity, we examined the variance inflation factor (VIF) to confirm if all relationships had a VIF of less than the critical collinearity issue indicator of 5 (Hair et al., 2019). This was followed with bootstrapping to confirm the statistical significance of the relationships being studied. To assess the predictive power of the study model, we reviewed the Q^2 measure where positive Q^2 values ($Q^2 > 0$) would indicate a good predictive power and negative Q^2 values ($Q^2 < 0$) would indicate the opposite.

CHAPTER 4: DATA ANALYSIS AND RESULTS

This chapter presents the results of the data analysis. A description of the sample and preliminary data screening is shared, followed by the assessment of the measurement model to establish indicator reliability, internal consistency reliability, convergent validity, and discriminant validity. The structural model is then evaluated to test the proposed hypotheses, the direct relationships and the interaction effects. A report of the key model indicators is also presented. This chapter provides the statistical evidence utilized in the discussion and interpretation of findings in chapter 5.

The survey yielded 337 total responses of which, 297 were deemed fit for analysis after data cleansing was done. All responses were solicited from individuals working either as fulltime or parttime employees in companies that were based in the United States. There were 38 respondents who started but did not complete the survey because they either abandoned the survey midway or, were screened out automatically based on their responses to the first three questions. These questions were:

Q1. Are you currently employed (either full-time or part-time)?

Q2. Do you actively use Artificial Intelligence (AI) at your workplace?

Q3. Does your company / place of employment intend to start using Artificial Intelligence (AI)?

In addition, there were 2 respondents who failed the attention checker questions whose responses were also dropped from the dataset. To further ensure data quality and the validity of the measurement model, an additional diagnostic check for straight-lining, the consecutive selection of identical Likert-scale options as responses, was conducted. This procedure was essential to eliminate the possibility of indicator redundancy which could inflate internal consistency reliability beyond the recommended threshold (Hair et al., 2020; Sarstedt et al., 2021). Straight-lining was not observed in the dataset. The survey instrument had the forced response format enforced, requiring all items to be answered prior to submission which ensured there were no missing values in the dataset.

As part of the survey, several demographic variables were captured, including gender, age, tenure, overall work experience in years, role in the company and the industry in which the respondent works. Out of the 297 respondents, 132 (44.40%) were female, 164 (54.40%) were male and 1 (0.30%) responded as Non-Binary. 7 (2.40%) individuals identified themselves as entry level employees, 87 (29.30%) as Individual contributors, 142 (47.80%) as managers or team leads, 37 (12.50%) as senior managers, and 24 (8.10%) as C-Level management in their roles. Below is a table illustrating the demographic composition of the sample.

Table 1: Respondents Demographic Data (n=297)

Characteristic	Value, n	%
Gender		
Male	164	55.22%
Female	132	44.44%
Non-Binary	1	0.34%
Role		
Entry Level	7	2.36%
Individual Contributor	87	29.29%
Manager / Team Lead	142	47.81%
Senior Manager	37	12.46%
C-Level / Executive Management	24	8.08%
Industry		
Banking / Finance	65	21.89%
Education	56	18.86%
Government / Public Service	4	1.35%
Health Care	20	6.73%
Hospitality / travel	11	3.70%
Manufacturing	34	11.45%
Media / Entertainment	16	5.39%
Professional Services	14	4.71%

Respondents Demographic Data (n=297), (continued)

Retail / Consumer Goods	54	18.18%
Technology / IT	8	2.69%
Other	15	5.05%

The respondents also varied in age, how long they had been working for the company and their overall work experience time. The average age of the respondents was 41.3 years, the average time spent in the company, was 9.1 years, and the average work experience in years was recorded as 18.9 years. Below is a summary of the age, tenure and work experience years for the respondents.

Table 2: Additional Demographic Data

Characteristic	**Min**	**Max**	**Mean**	**Median**	**Standard deviation**
Age (yrs)	25	60	41.316	40	8.807
Tenure (yrs)	0	38	9.192	7	6.911
Work Experience (yrs)	1	46	18.912	19	9.226

Prior to importing the dataset into SmartPLS 4, several control variables were recoded to ensure the model better fits the observed data and to enhance interpretation. Role was collapsed from five categories into three meaningful groups: Individual Contributor (entry-level and individual contributor), Manager / Team Lead, and Senior Management (senior manager and C-Level). Two dummy variables were then created, Role_Individual and Role_SrMgmt, with Role_Mgr (Manager / Team lead) treated as the reference category. To control for sector specific variance while maintaining statistical power, the industry variable was recoded into a binary indicator. Manufacturing and retail / consumer goods were combined into non-service industries, and all other categories were combined as service industries. This was dummy coded as Industry_Non-Service using service industries as the reference category. Lastly, gender was coded as a binary control variable, with G_Female coded as 1 and the comparison group coded as 0. These recoded variables were then included as single-item controls in the structural model.

SmartPLS version 4 was used to evaluate the measurement model and structural model using partial least squares structural equation modeling (PLS-SEM). The reflective model included 40 indicators for the 4 latent variables and 7 control variables. This study followed the confirmatory composite analysis (CCA) procedure for reflective measurement models, recommended for PLS-SEM (Hair et al., 2020). As the first step, we examined the standardized indicator outer loadings and their statistical significance for all the constructs to ensure they met the minimum recommended threshold of 0.70, which indicates that the construct explains more than 50% of the indicator's variance, establishing indicator reliability. The following describes the measurement model analysis for each of the 4 constructs.

4.1 Behavioral Intention to Adopt AI

Behavioral intention to adopt AI (BI) was evaluated as a reflective construct. The results are depicted in the table below.

Table 3: Behavioral Intention Indicator Outer-loadings and reliability values

Construct	Outer loadings	T-Statistics	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Behavioral Intention			0.931	0.940	0.956	0.879
BI_1 <- BI	0.971	134.547				
BI_2 <- BI	0.902	37.235				
BI_3 <- BI	0.938	47.184				

All indicators for the BI construct showed strong loadings (0.902, 0.938, and 0.971) greater than the recommended 0.708 and showed statistical significance based on the bootstrapping calculations (t = 37.235, t = 47.184, and t = 134.547) supporting indicator reliability. The results indicated that internal consistency reliability was also established with Cronbach's alpha (α = 0.931), composite reliability rho_a (ρA= 0.940), and composite reliability rho_c (ρc = 0.956) all exceeding the accepted 0.70 lower limit (Hair et al., 2020). Finally, convergent validity was also confirmed as the average variance extracted (AVE = 0.879) was higher than the 0.50 criterion (Hair et al., 2020). Although the composite reliability rho_c was slightly higher than the recommended 0.95, all indicators were retained to preserve content coverage and maintain comparability with established UTAUT operationalizations of behavioral intention of technology adoption (Venkatesh et al., 2003; Venkatesh et al., 2012).

4.2 Perceived Risks

The quality of the measured perceived risk (PR) construct was also evaluated as a reflective construct following the systematic procedures for reflective measurement models. The construct was operationalized with 14 indicators which reflected performance risks, privacy risks, psychological risks, and time risks. The initial outer loadings and reliability results for the construct and the indicators are depicted in the table below.

Table 4: Perceived Risks indicator outer-loadings and reliability values

Construct	Outer loadings	T-Statistics	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Perceived Risks			0.935	0.95	0.94	0.531
PR_Perf_1 ← PR	0.701	19.182				
PR_Perf_2 ← PR	0.76	23.196				
PR_Perf_3 ← PR	0.762	23.719				
PR_Perf_4 ← PR	0.778	26.232				
PR_Perf_5 ← PR	0.693	17.117				
PR_Priv_1 ← PR	0.678	15.629				
PR_Priv_2 ← PR	0.71	17.369				
PR_Priv_3 ← PR	0.616	12.025				
PR_Psy_1 ← PR	0.718	23.92				
PR_Psy_2 ← PR	0.729	25.741				
PR_Time_1 ← PR	0.701	20.813				
PR_Time_2 ← PR	0.789	31.537				

Table 5: Perceived Risks indicator outer-loadings and reliability values (continued)

PR_Time_3 ← PR	0.782	30.493
PR_Time_4 ← PR	0.771	26.726

The assessment of the indicator reliability indicated that while all standardized outer loadings were statistically significant ($t > 1.96$), several indicators had a weaker loading below the desired threshold of 0.708, i.e., 0.616, 0.678, and 0.693. The corresponding survey items that were removed are:

PR_Perf_5: The AI system may not perform reliably and could produce incorrect outcomes or errors.

PR_Priv_1: There is a chance that using the AI system will cause me to lose control over my personal data or private information.

PR_Priv_3: Cybercriminals might gain unauthorized access to my personal data if I use this AI system.

Considering the construct had an average variance extracted (AVE) = 0.531, above the minimum threshold of 0.50, I did not consider removing any of the indicators for convergent validity reasons. With an AVE = 0.531, convergent validity was confirmed which means the construct explains 53% of the variance of its indicators. The results also indicated that estimated measurement model showed satisfactory internal consistency reliability, with Cronbach's alpha ($\alpha = 0.935$), Composite reliability rho_a ($\rho A = 0.950$), and composite reliability rho_c ($\rho c = 0.940$), all within the recommended range of 0.70 and 0.95 (Hair et al., 2020).

4.3 Social Influence

The social influence (SI) construct was initially operationalized with 7 indicators. The initial outer loadings and reliability results for the construct and the indicators are depicted in the table below.

Table 6: Social Influence indicator outer-loadings and reliability values

Construct	Outer loadings	T-Statistics	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Social Influence			0.827	0.872	0.855	0.462
SI_Image_1 ← SI	0.581	7.162				
SI_Image_2 ← SI	0.661	8.961				
SI_Image_3 ← SI	0.562	7.038				
SI_SF_1 ← SI	0.580	9.561				
SI_SF_2 ← SI	0.739	22.212				
SI_SN_1 ← SI	0.802	23.558				
SI_SN_2 ← SI	0.787	21.958				

The initial assessment of the indicator reliability indicated that all standardized outer loadings were statistically significant ($t > 1.96$). While some were above the recommended threshold of 0.708, other indicator loadings fell short of the ideal threshold, ranging between 0.562 to 0.661. The results indicated internal consistency reliability was also established and satisfactory, within the acceptable range of 0.70 as the lower limit and 0.95 as the upper limit, with Cronbach's alpha ($\alpha = 0.827$), Composite reliability rho_a ($\rho A = 0.872$), and composite reliability rho_c ($\rho c = 0.855$). Convergent validity, which was assessed by the average variance extracted, AVE=0.462, was below the recommended minimum of 0.50 which suggested that the SI construct did not yet capture sufficient variance across its indicators. Following PLS-SEM measurement guidelines of removing indicators with lowest loadings one at a time (Hair et al., 2020), the SI_Image_3 followed by SI_Image_1indicators were removed until a favorable convergent validity was achieved with a new AVE = 0.519. The survey items that were removed were:

SI_Image_1: People in my organization who use AI have more prestige than those who do not.

SI_Image_3: Having or using AI is a status symbol in my organization.

After the removal of the two indicators, the model was re-estimated. The results of the refined 5 item social influence construct are depicted in the table below.

Table 7: Refined Social Influence final indicator outer-loadings and reliability values

Construct	Outer loadings	T-Statistics	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Social Influence			0.77	0.831	0.84	0.519
SI_Image_2 ← SI	0.564	8.423				
SI_SF_1 ← SI	0.568	8.705				
SI_SF_2 ← SI	0.787	33.889				
SI_SN_1 ← SI	0.822	25.536				
SI_SN_2 ← SI	0.81	23.463				

The two indicators that had weak loadings were retained because the convergent reliability at the construct level was established, AVE=0.519, and the items were deemed meaningful in capturing facets of social influence. The newly estimated model also showed satisfactory internal consistency reliability, with Cronbach's alpha ($\alpha = 0.77$), Composite reliability rho_a ($\rho A =$ 0.831), and composite reliability rho_c ($\rho c = 0.84$.).

4.4 Organizational Trust

Consistent with the other constructs, the reflectively measured organization trust (OT) construct was also evaluated following the systematic CCA procedures recommended by Hair et al., (2020). The construct was initially operationalized with 16 indicators. The initial outer loadings and reliability results for the construct and the indicators are depicted in the table below.

Table 8: Organizational Trust indicator outer-loadings and reliability values

Construct	Outer loadings	T-Statistics	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Organizational Trust			0.969	0.977	0.972	0.683
OT_Benev_1 ← OT	0.814	26.234				
OT_Benev_2 ← OT	0.848	36.420				
OT_Benev_3 ← OT	0.747	19.651				

OT_Benev_4 ← OT	0.857	31.151
OT_Benev_5 ← OT	0.824	31.684
OT_Comp_1 ← OT	0.865	40.381
OT_Comp_2 ← OT	0.828	32.471
OT_Comp_3 ← OT	0.831	37.262
OT_Comp_4 ← OT	0.894	60.708
OT_Comp_5 ← OT	0.833	34.883
OT_Comp_6 ← OT	0.855	42.386
OT_Integr_1 ← OT	0.819	26.929
OT_Integr_2 ← OT	0.662	12.439
OT_Integr_3 ← OT	0.815	31.092
OT_Integr_4 ← OT	0.843	34.738
OT_Integr_5 ← OT	0.864	43.853

Indicator reliability was assessed using outer loadings. Except for one indicator, OT_Integr_2 (loading = 0.662), all other indicators were above the recommended threshold of 0.708 with loadings ranging from 0.747 to 0.894. The indicator item that had a loading less that 0.708 was:

OT_Integr_2: I never have to wonder whether top management will stick to its word

All indicators associated with the OT construct, showed statistical significance ($t > 1.96$) which was confirmed from the bootstrapping results. This showed indicator reliability under the common reflective guideline (Hair et al., 2019; Hair et al., 2020). Having established the construct's convergent validity, with the average variance extracted (AVE = 0.683), the OT_Integr_2 indicator was not deleted because the construct explains a satisfactory amount of variance being above the acceptable 0.50 criterion (Hair et al., 2020). The internal consistency reliability metrics, Cronbach's alpha ($\alpha = 0.969$), composite reliability rho_a ($\rho A = 0.979$), and composite reliability rho_C ($\rho c = 0.972$) all exceeded the 0.95 threshold which are considered problematic in PLS-SEM (Hair et al., 2020). Such high reliability values suggest existence of overlap between items on the construct. To address the item redundancy and attempt to achieve a satisfactory internal consistency reliability, a model refinement was conducted following the Hair et al., (2020) recommendations. A review of the items was conducted and several items

(OT_Comp_1, OT_Comp_3, OT_Comp_5, OT_Comp_6, OT_Benev_1 and OT_Benev_2; OT_Integr_1, OT_Integr_2, OT_Integr_3) were dropped from the model. The refinement aimed to retain only the items that were uniquely capturing content coverage to enhance content validity. The newly refined 7 item model was re-estimated, and the results are presented in the table below.

Table 9: Refined Organizational Trust final indicator outer-loadings and reliability values

Construct	Outer loadings	T-Statistics	Cronbach's alpha (α)	Composite reliability (rho_a)	Composite reliability (rho_c)	Average variance extracted (AVE)
Organizational Trust			0.939	0.956	0.95	0.729
OT_Benev_3 ← OT	0.780	21.124				
OT_Benev_4 ← OT	0.873	30.802				
OT_Benev_5 ← OT	0.849	33.769				
OT_Comp_2 ← OT	0.834	28.409				
OT_Comp_4 ← OT	0.891	50.484				
OT_Integr_4 ← OT	0.865	34.803				
OT_Integr_5 ← OT	0.881	42.256				

The refinements successfully improved internal consistency reliability to acceptable levels (α = 0.939, ρA = 0.956, ρc = 0.95). While composite reliability rho_a remains slightly above target, the metrics collectively represent a more diverse measurement model. Convergent validity was also improved with a final AVE = 0.729 implying the construct explains 73% of its indicator's variance. All remaining standardized outer loadings were above the minimum threshold supporting a strong indicator reliability. The final Indicators, their loadings, path coefficients and R^2 are depicted below.

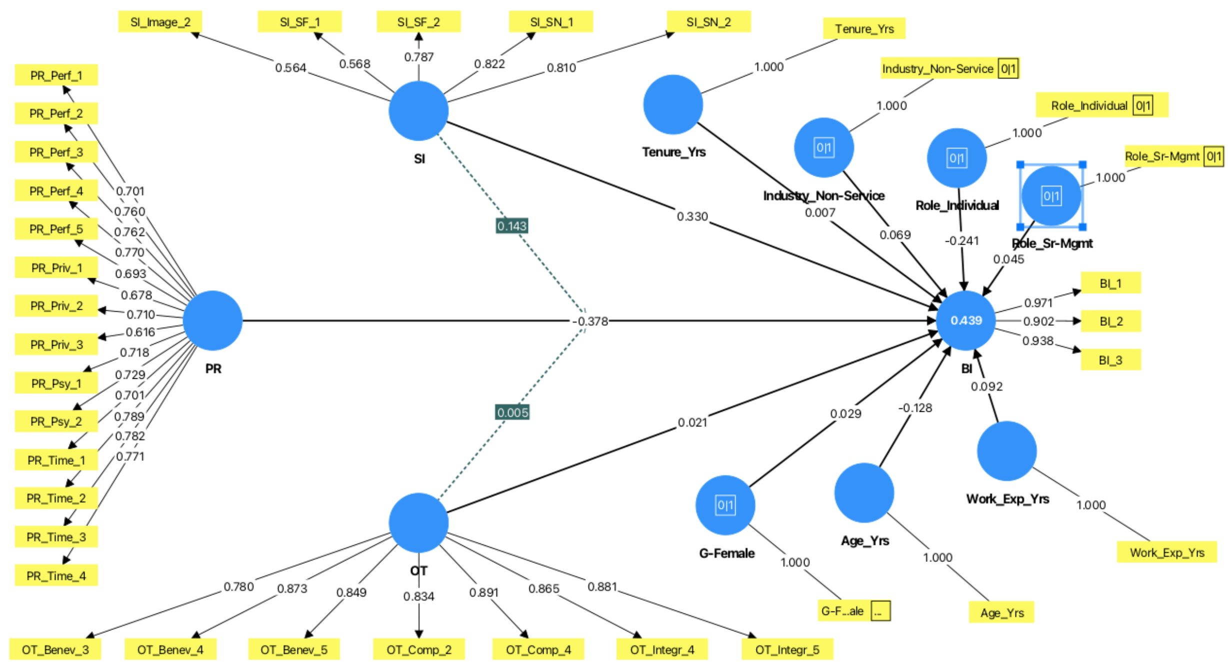

Figure 3: Final PLS-SEM measurement model indicating path coefficients and the R^2 values

After establishing indicator reliability, internal consistency reliability, and convergent validity, the next step in the measurement model assessment process was to evaluate the discriminant validity to confirm that each of the latent variables captures a conceptually unique and distinct response. Discriminant validity examines whether a reflective construct exhibits stronger relationships with its own indicators than those of other constructs in the PLS-SEM Model, (Hair et al., 2022). To verify the discriminant validity of the model, we used the Heterotrait-Monotrait ratio of correlations (HTMT) (Henseler, Ringle, & Sarstedt, 2015).

Table 10: HTMT Ratios

Constructs	Heterotrait-Monotrait ratio (HTMT)
OT ⇔ BI	0.225
PR ⇔ BI	0.487
PR ⇔ OT	0.319
SI ⇔ BI	0.558
SI ⇔ OT	0.232
SI ⇔ PR	0.324

As indicated in the above table, all HTMT ratios (ranging from 0.225 to 0.558) were well below the recommended threshold of 0.85 confirming discriminant validity is supported for BI, PR, OT and SI constructs. This study also checked the bootstrapped HTMT confidence intervals and confirmed none of the construct pairs confidence intervals was close to 1.0, as shown in the table below, which further confirmed that discriminant validity was supported in our model.

Table 11: HTMT Inference (bootstrapped 95% CI)

Construct Pairs	**Original sample (O)**	**Sample mean (M)**	**2.50%**	**97.50%**
OT ⇔ BI	0.225	0.226	0.132	0.323
PR ⇔ BI	0.487	0.486	0.385	0.577
PR ⇔ OT	0.319	0.319	0.196	0.436
SI ⇔ BI	0.558	0.559	0.459	0.652
SI ⇔ OT	0.232	0.248	0.146	0.370
SI ⇔ PR	0.324	0.344	0.248	0.448

Following the establishment of discriminant validity, nomological validity was assessed by checking whether the constructs exhibited patterns of relationship that were hypothesized and predicted in theory within the model. The study examined the latent variable correlation table as shown in the table 11.

Table 12: Latent Variable Correlations

Variables	***Age_ Yrs***	***BI***	***G-Female***	***Industry _Non-Service***	***OT***	***PR***	***Role_ Individual***	***Role_ Sr-Mgmt.***	***SI***	***Tenure _Yrs***	***Work_ Exp_Yrs***
Age_Yrs											
BI	0.033										
G-Female	0.045	-0.034									
Industry_Non-Service	0.167	0.05	-0.108								
OT	0.075	0.222	0.028	0.107							
PR	-0.092	-0.512***	0.077	-0.045	-0.304						
Role_Individual	-0.26	-0.221*	0.06	-0.14	-0.129	0.113					
Role_Sr-Mgmt	0.185	0.109	-0.037	0.126	0.2	-0.052	-0.346				
SI	0.003	0.514***	-0.055	-0.03	0.232	-0.33	-0.149	0.047			
Tenure_Yrs	0.422	0.081	-0.128	0.101	0.086	-0.082	-0.262	0.202	0.079		
Work_Exp_Yrs	0.831	0.033	0.000	0.199	0.043	-0.039	-0.264	0.234	-0.033	0.402	

As indicated in table 11, the correlations between the constructs align with the study's nomological network. Perceived risks exhibited a strong negative correlation with behavioral intention (β = -0.378, $p < 0.001$), while social influence showed a strong positive correlation with behavioral intention (β = 0.330, $p < 0.001$). Additionally, we accounted for several control variables (Age, Gender, Industry, Role, Tenure and years of Work Experience). Role_Individual was the only control variable that showed statistical significance ($p = 0.021$). Below is a depiction of the structural model indicating significance on the paths based on the bootstrapping procedure.

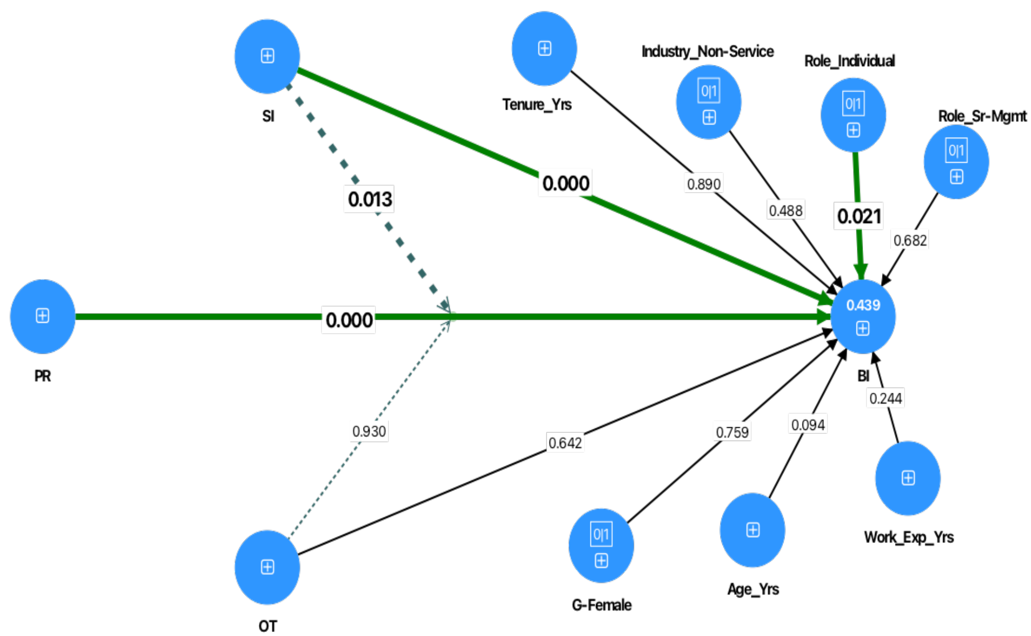

Figure 4: Structural Model Results Showing Path Significance ($p < 0.05$ paths are highlighted)

This study also evaluated the direction, magnitude, and statistical significance of the hypothesized path coefficients using a bootstrapping procedure with 10000 samples. The results are shown in Table 12 below.

Table 13: Path Analysis and Hypotheses Testing Results

Variables	Path coefficient (β)	Standard error	T statistics	P values
H1: PR → BI	-0.378	0.041	9.176	0.000
H2: SI → BI	0.330	0.049	6.726	0.000
H3: OT → BI	0.021	0.046	0.465	0.642
H4: SI x PR → BI	0.143	0.058	2.492	0.013
H5: OT x PR → BI	0.005	0.053	0.088	0.930
Age_Yrs → BI	-0.128	0.077	1.675	0.094
G-Female → BI	0.029	0.094	0.307	0.759
Industry_Non-Service → BI	0.069	0.099	0.693	0.488
Role_Individual → BI	-0.241	0.104	2.314	0.021
Role_Sr-Mgmt → BI	0.045	0.110	0.410	0.682
Tenure_Yrs → BI	0.007	0.048	0.138	0.890
Work_Exp_Yrs → BI	0.092	0.079	1.166	0.244

The were consistent with the theoretical direction and expected size of the correlations, therefore nomological validity was confirmed as shown in table above.

H_1 PR→BI, ($\beta = -0.378$, $t = 9.176$, $p < 0.001$), the relationship appears strong, significant and negative as predicted.

H_2 SI→BI, ($\beta = 0.330$, $t = 6.726$, $p < 0.001$), the relationship also appears strong, significant and positive as predicted.

H_3 OT→BI, ($\beta = 0.021$, $t = 0.465$, $p = 0.642$), the relation was not significant, and the hypothesis was not supported.

H_4 SI x PR→BI, ($\beta = 0.143$, $t = 2.492$, $p = 0.013$), there is significant moderation and the positive direction implies the negative PR→BI relationship becomes weaker when SI is higher.

H_5 OT x PR →BI, ($\beta = 0.005$, $t = 0.088$, $p = 0.930$), not significant, no moderation and the hypothesis was not supported.

The results indicate support for the proposed nomological network linking perceived risk and social influence on behavioral intention to adopt AI. As expected, PR was negatively associated with BI, SI was positively associated with BI and, in addition, the interaction effect between SI and PR was statistically significant indicating the relationship between PR and BI varies as a function of SI. From the results, the direct effect of OT on BI and its interaction with PR were not supported. Overall, the observed structural relationships are consistent with the theoretical expectations for the core predictors of BI, the significance and direction of the structural paths further support the nomological validity of the constructs within the final for the model.

Upon the successful confirmation of the reflective measurement models, the structural model was evaluated in accordance with the second stage of the CCA (Hair et al., 2020). The first step involved checking for inner model collinearity to ensure that high correlations between predictor constructs did not bias the path coefficients (Hair et al., 2020). The table below shows the collinearity statistics (VIF – inner model) for the key relationships in the structural model.

Table 14: Collinearity Statistics – Inner Model VIF

Variables	Collinearity Statistics VIF - Inner Model
OT → BI	1.248
OT x PR → BI	1.154
PR → BI	1.225
SI → BI	1.318
SI x PR → BI	1.218

As shown in the table above, all inner model VIF values (ranging from 1.154 to 1.318) were well below the conservative threshold of 3.0 confirming multicollinearity was not a critical issue and allowing for reliable interpretation of the structural relationships. The VIFs were also checked for analysis of common method bias (CMB), considering they were well below the threshold of 3.3, common method bias was not a concern (Kock, 2015).

Based on the assessment of this structural model, behavioral intention to adopt AI (BI) was explained to a meaningful degree (R^2= 0.439) and the model demonstrated a strong predictive relevance (Q^2 = 0.360). Consistent with the proposed nomological network, perceived risk has a strong negative effect on BI (β = -0.378, t = 9.176, p < 0.001), while social influence had a strong positive effect on BI (β = 0.330, t = 6.726, p < 0.001). The interaction between social influence and perceived risk was also significant (β = 0.143, t = 2.492, p = 0.013), indicating that the interaction between PR and BI varies as a function of social influence. In contrast, organizational trust did not exhibit a significant direct effect on BI (β = 0.021, p = 0.465) and did not significantly moderate the PR and BI relationship (β = 0.005, p = 0.930). Next, we examined the out of sample predictive power by applying the PLS predict method and comparing the results on two benchmarks: the Q^2 value and the linear model (LM).

Table 15: PLSPredict and Standard Error Estimates Results

	Q^2predict	**PLS-SEM_RMSE**	**PLS-SEM_MAE**	**LM_RMSE**	**LM_MAE**	**IA_RMSE**	**IA_MAE**
BI_1	0.353	0.876	0.666	0.864	0.652	1.089	0.760
BI_2	0.219	0.887	0.653	0.851	0.638	1.004	0.671
BI_3	0.348	0.899	0.667	0.933	0.670	1.113	0.743

The positive Q^2 predict values (BI_1 = 0.353; BI_2 = 0.219; BI_3 = 0.348) indicate the model has a good out-of-sample predictive power and provides better predictive performance than simply using mean values. We used the Root Mean Squared Error (RMSE) for quantifying the prediction error by comparing the PLS-SEM_RMSE for each of the indicators against the LM_RMSE benchmark. Two of the indicators (BI_1 and BI_2) had slightly higher PLS-SEM_RMSE values when compared to the LM_RMSE while one (BI_3) was lower. Based on this, only a minority of the dependent variable indicators yielded smaller prediction errors, the model was considered to have low predictive power. Nonetheless, the out of sample prediction assessment using PLSPredict supported predictive relevance for BI with positive Q^2 predict values across all BI indicators (0.219 – 0.353).

The results of the structural model analysis and the specific outcomes for each of the proposed hypotheses are summarized in the table below.

Table 16: Summarized Hypotheses Results

Hypothesis	**Path coefficient (β)**	**T statistics**	**P values**	**Results**
H1: PR → BI	-0.379	9.08	0.000	Supported
H2: SI → BI	0.336	6.692	0.000	Supported
H3: OT → BI	0.023	0.511	0.61	Not Supported
H4: SI x PR → BI	0.144	2.517	0.012	Supported
H5: OT x PR → BI	0.006	0.115	0.908	Not Supported

CHAPTER 5: DISCUSSION, IMPLICATIONS, AND CONCLUSIONS

This chapter discusses the results, which are situated within the broader scholarly literature on organizational adoption of artificial intelligence and related emerging technologies, reported in Chapter 4. The chapter begins by summarizing the study purpose, research questions, and methodological approach, followed by a concise summary of the key measurement and structural model results. It then interprets the structural model findings in relation to the proposed hypotheses, highlighting supported and unsupported relationships. The next section discusses the theoretical contributions and practical implications of the findings for organizational leaders and AI adoption initiatives. The chapter will conclude after a section addressing limitations and offering suggestions for future research.

This study set out to investigate the perceptions affecting employees' intention to adopt artificial intelligence at the workplace. Specifically, the study tested whether employees' perceived risk is negatively associated with their intention to adopt AI and whether social influence and organizational trust serve as moderators of this relationship in organizational contexts. Understanding these determinants is important because organizations realize the benefits of technology investments only when new systems are accepted and used by employees (Venkatesh & Davis, 2000).

To examine employees' behavioral intention to adopt artificial intelligence in workplace settings, the study employed a quantitative survey design using a survey instrument that adapted items from established, validated scales utilized in prior research. The data were collected via an online survey administered through the Qualtrics online platform. The survey instrument included an IRB approved consent statement and acknowledgment item, screening questions and the study's measurements and demographic items. The participants were recruited using Prolific, an online research platform that connects researchers with diverse, prescreened, and verified respondents. To be eligible to participate, the respondents were required to be employed adults working in companies based in the United States (U.S.A), employed by an organization that currently uses AI or intends to implement AI in the near future, and to report that they personally use AI at work or intend to use it in the near future. Eligible respondents who accepted the Prolific invitation were redirected to Qualtrics to complete the survey. After data screening and quality checks, the final usable sample included N = 297 participants. The survey instrument included demographic and work-related items; age, gender, tenure, work experience, role, and industry, that were used as control variables in the study.

The data collected were analyzed using partial least squares structural equation modeling (PLS-SEM) using SmartPLS version 4 software. The study followed the two-stage process recommended to effectively analyze data using PLS-SEM (Sarstedt et al., 2021; Hair et al., 2020). The analysis began with the thorough assessment of the measurement models before evaluating the structural model. To evaluate and confirm the quality of the reflective measurement models, the confirmatory composite analysis (CCA) 7-step process as recommended by Hair et al. (2020) was used. First, the indicator reliability was evaluated by examining the indicator outer loadings, and in the internal consistency reliability, assessing the Cronbachs alpha, the exact reliability coefficient (rho_A), and the composite reliability (rho_c). Second, convergent validity was established using the average variance extracted (AVE) to ensure the minimum threshold of 0.50 (Hair et al., 2020) was achieved. Thereafter, discriminant validity was confirmed using the Hererotrait-Monotrait ratio of correlations (HTMT) by confirming each construct did not exceed the conservative threshold, 0.85 (Hair et al., 2020), ensuring their distinctiveness. After confirming the discriminant validity, nomological validity was assessed providing an additional validation of construct validity. Finally, for the first stage, predictive validity was conducted to assess the extent to which the model could be used to predict future outcomes. During the CCA process, refinement of several construct indicators was conducted to realize measurement model results that supported indicator reliability, internal consistency reliability, convergent validity, discriminant validity, nomological validity, and predictive validity recommended threshold and defined in the CCA process by Sarstedt et al., (2021). This confirms the latent variables were measured with acceptable reliability and captured distinct concepts.

Once the measurement models were confirmed, the second stage, the evaluation of the structural model, tested the hypothesized relationships. First, the inner model collinearity was assessed using the variance of inflation factor (VIF) values, ensuring they remained below the recommended threshold of 3.0 to prevent bias (Hair et al., 2020). Second, the standardized path coefficients (Beta) and their significance were estimated using a bootstrapping procedure with 10000 samples. The model's performance was evaluated across 3 dimensions: First, explanatory power was assessed using the coefficient of determinations (R^2). Second, in-sample predictive relevance was assessed using the blindfolding-based Q^2 value. And third, out-of-sample predictive power was evaluated using the PLSpredict procedure, comparing the resulting model prediction errors against the linear model benchmark (Hair et al., 2020).

The structural model results supported our first hypothesis (H_1), perceived risk (PR) was negatively and significantly associated with behavioral intention (BI) to adopt AI (PR → BI; $\beta = -0.379$, $p < 0.001$). H_2 was also supported with results indicating social influence (SI) was positively and significantly associated with BI (SI → BI; $\beta = 0.336$, $p < 0.001$). In addition, the interaction between SI and PR was also statistically significant (SI x PR → BI; $\beta = 0.144$, p =

0.012) supporting H_4 and indicating that higher SI attenuates the negative association between PR and BI. In contrast, organizational trust (OT) was not significantly associated with behavioral intention (OT → BI; $\beta = 0.023$, $p = 0.610$) and the interaction between OT and PR was also not significant (OT x PR → BI; $\beta = 0.006$, $p = 0.908$) negating support for H_3 and H_5 respectively. The proportion of variance in the BI to adopt AI, with an $R^2 = 0.435$, was explained meaningfully by the model. With $Q^2 = 0.411$, predictive relevance was supported confirming a strong in-sample predictive capability. Finally, out-of-sample predictive power was supported with positive Q2predict positive values indicated by the PLSpredict results.

Increasingly, organizations are making strides towards the adoption of emerging technologies, like AI, as they seek to increase efficiency, improve execution while reducing costs (Arora et al., 2023; Fang et al., 2021; Wang et al., 2023). At the same time, the efforts towards adoption can generate salient employee concerns and fears that may impede the efforts management teams put towards realizing benefits of AI technologies. These concerns and fears, including perceived risks related to privacy, security, bias, opaqueness, accountability etc. (Bankins &Formasa, 2023; Richardson et al., 2021) underscore the importance of understanding factors shaping employees intentions to adopt these technologies. The results from this study provide strong support for hypothesis 1 (H_1), confirming perceived risk (PR) acts as a barrier to the employee's behavioral intention (BI) to adopt AI. Specifically, the findings confirmed that PR is a strong and significant negative predictor of the behavioral intention to adopt AI. Considering BI serves as a strong predictor for use (Ajzen, 1991; Venkatesh et al., 2003; Venkatesh et al., 2012), these results assert that PR has the potential to impede the use of AI in organizations if not mitigated. The negative relationship aligns with previous established research that indicates employees are likely to engage in protective behavior which reduces their desire to adopt (Schwesig, 2023; Bankins & Formosa, 2023; Gerlich, 2023). Being multidimensional in nature, perceived risks can include performance related risks, privacy risks, psychological concerns, or time risks (Featherman & Pavlou, 2003) which could affect each individual employees differently and with varying magnitudes. These risks can be difficult to identify without intentionality by the management team since AI systems can be opaque and lack transparency producing consequential results for the employees, the AI users of the organization (Bankins & Formosa, 2023). Consequently, while value for AI can be recognized, employees' perceives risks towards the technology may act a significant inhibitor for adoption. Adoption efforts by the management team must go beyond deploying the technology and instructing employees to use it. It must also include training, proper communication for assurance, safeguards and governance structures like policies on how to safely use the technology responsibly and ethically. These could help reduce anxiety, fears and concerns on employees who would otherwise be inundated with perceived risks of the technology improving adoption and subsequent use realizing the anticipated efficiency and productivity gains.

Consistent with the established Unified Theory of Acceptance and Use of Technology (UTAUT) (Venkatesh et al., 2003), the findings in this study indicate that social influence (SI) has a positive and statistically significant relationship with the behavioral intention (BI) for AI adoption supporting our second hypothesis. In organizational settings, AI use is often visible through workflows, automations, performance expectations, lessons shared by peers amongst other ways asserting that social pressures can contribute to the influence of use or intention to use (Kulviwat et al., 2009). To avoid standing out, employees may be motivated to conform to established group norms, including use of AI, thereby establishing their sense of belonging (Eckhardt et al., 2009). The findings of this study are consistent with prior research, which found that employees are likely to observe peers' behaviors and anticipate their manager's expectations of their use of technology (Kulviwat et al., 2009). This adaptation to expectations and compliance to expected norms motivates the employees to align with what is viewed as the expected normal behavior at the workplace, in this case, intending to use AI as technology that others are using. Social comparisons may also contribute to pressures for employees to conform to the social norms and avoid deviating from the group norm enhancing AI adoption for some employees (Eckhardt et al., 2009). These mechanisms explain the observed positive association between social influence and AI adoption intention. Leaders in organizations can intentionally shape the social environment around AI by facilitating opportunities for positive peer influence. This can be done by identifying power users and providing them with a platform to evangelize the technology positively. Leadership endorsement and visible support can increase social pressure in the workplace leading to increased adoption. By using working or successful use cases as examples of AI deployments within the workplace, social influence can be established especially if done by credible peer champions who will be seen as peers to most employees as opposed to being conducted by senior managers. As the use of AI becomes more publicly observable rather than private use, social influence will drive more employees' intent of use (Kulviwat et al., 2009).

The fourth hypothesis (H_4) in this study, which tested the SI x PR interaction effect, was also supported with a positive and statistically significant finding ($\beta = 0.144$, $p = 0.012$). These results indicate that SI significantly weakens the negative association between PR and BI, the stronger the social influence is for an employee, the effect of their perceived risks towards AI will be reduced and subsequently increasing their intention to adopt AI. Conversely, where social influence is absent or weak, the negative effect of perceived risk diminishes the intention to adopt AI. This social influence can result from pressures emanating from supervisors, visible peer usage or supporting team norms. Consistent with prior research, social influence has a positive association with intentions of adoption (Venkatesh et al., 2003). In organizational settings, employees not only consider their own risk perceptions but also the normative expectations and informational cues provided by peers and managers (Kulviwat et al., 2009). High levels of social influence can facilitate internalization, a process where employees integrate the favorable beliefs of respected colleagues into their own value systems. The positive interaction effect (SI x PR → BI; $\beta = 0.144$) acting upon the negative direct relationship (PR → BI; $\beta = -0.379$) indicates the moderation effect attenuates (weakens) the primary relationship (PR → BI) (Hair et al., 2022, Sarstedt et al., 2021). When social influence is high, normative endorsement and peer pressure can increase the perceived benefits of AI and reduce uncertainty, reducing the impact of perceived risks on behavioral intentions of AI adoption. The findings suggest that organizations may partially mitigate risk-related resistance by shaping adoption norms positively through credible peer champions, leading to internalization as the advocated behavior is endorsed by credible experts (Karahanna et al., 1999; Maruping et al., 2017). Additionally, showcasing successful use cases and visible management endorsement is likely to increase social visibility providing reassurance and social support that offsets individual uncertainties and fears.

H_3 and H_5, contrary to expectations resulted in non-significant relationship and interaction effects. In both cases, the hypotheses were not supported indicating that organizational trust (OT) did not have a significant relationship with behavioral intention to adopt AI and does not meaningfully change the relationship between perceived risk and intention to adopt AI. These results should not be taken to mean organizational trust, often grounded in perceptions of leadership competence, integrity and benevolence (Mayer et al., 1995) is unimportant in the processes associated with technology adoption. Instead, they suggest trust may matter under certain conditions or may influence adoption in less direct ways than those tested in this study. OT is reflected in employees' willingness to accept and rely on information provided by the management team especially in in conditions of uncertainty (Huurne & Gutteling, 2008). OT also involves judgments on whether the leadership team demonstrates competence, integrity, and benevolence (Bachmann & Inkpen, 2011). These judgments are value based and may be interpreted differently by each employee rendering trust to operate as a broader organizational cultural factor rather than an immediate driver of whether a specific employee intends to adopt and use a specific technology. Trust promotes risk taking propensity as it increases employees' willingness to accept more vulnerability where outcomes are uncertain (Schoorman et al., 2007). As such, in the context of AI adoption intention, organizational trust may shape adoption intention by influencing employees' risk-taking orientation by reducing perceived risks or increasing confidence in organizational safeguards and oversight, rather than directly predicting the behavioral intention for adoption.

Control variables were included to account for alternative explanations related to demographic and work-context differences (age, gender, industry, tenure, and work experience, in addition to role). Among these controls, Role_Sr-Mgmt was the only control variable that showed a statistically significant association with behavioral intention to adopt AI, whereas the remaining controls were not significant. This suggests that differences in adoption intention may be more strongly tied to employees' organizational position than other basic demographic characteristics in this sample.

This study contributed to technology adoption and workplace AI research in three primary ways:

1. Social influence as a moderating influence of perceived risk in workplace AI adoption. This study provides evidence that social influence not only relates positively to behavioral intention but also attenuates the negative association between perceived risk and behavioral intention to adopt AI. The significant interaction effect indicates that when normative support and social expectations are stronger, perceived risk's strong negative association with adoption intention is reduced. This extends prior technology adoption research by demonstrating a specific buffering role for social influence in the perceived risk and behavioral intention relationship in organizational AI adoption contexts.
2. Boundary conditions for organizational trust in AI adoption intention models. Organizational trust did not show significant direct or moderating effects in this study, suggesting that its role in workplace AI adoption may be conditional or operate through indirect mechanisms rather than as a proximal determinant of intention. This null finding refines theoretical expectations by indicating that general organizational trust may not explain additional variance in AI adoption intention once perceived risk and social influence are considered. It's also feasible that the different dimension of organizational trust, competence, integrity, and benevolence, may impact behavioral intentions of adoptions differently.
3. Revalidation of risk-based explanations of AI adoption intention in organizational contexts. Perceived risk has been widely studied as an inhibitor of technology adoption; this study revalidates the negative association between perceived risk and behavioral

intention in the specific context of workplace AI adoption. By operationalizing perceived risk using established multidimensional conceptualizations and testing its relationship with intention in a contemporary AI setting, the findings reinforce the continued relevance of risk perceptions for understanding AI acceptance in organizations (Featherman & Pavlou, 2003; Martins et al., 2014).

The findings offer several practical implications for organizational leaders seeking to improve employee adoption of AI in their organizations. Given the strong negative link between perceived risk and employees' intention to adopt AI, organizations should address risk perceptions as a critical implementation priority rather than an afterthought. Practically, this entails putting clear safeguards in place, such as guidelines that define acceptable AI use, straightforward communication about privacy and data protections, communicate the job security, and accountability for decisions supported by AI. Training should also focus on safe-use practices for example, how to check AI outputs, when to seek escalation, and which activities should not rely on AI, because unresolved uncertainty and anxiety can directly suppress adoption intentions. Deliberate steps must be taken to ensure change management best practices are followed. Leaders should create opportunities for positive peer influence by identifying power users or champions and giving them visible platforms to demonstrate and advocate for effective AI use. The leadership teams' endorsement and visible support of AI during the adoption period is critical in signaling that AI use is valuable and expected to increase social normalization of the adoption of AI. Managers should be equipped to set clear, consistent expectations about AI use and to demonstrate appropriate adoption in their own work. This involves giving managers straightforward guidance on what effective and responsible use looks like, communicating expectations in a supportive manner, and ensuring employees know where to go for help when questions arise. Leadership encouragement should be complemented by facilitating conditions (Venkatesh et al., 2003), such as dedicated time for learning, access to approved tools, and clear guardrails, so that the social push to adopt is reinforced by the resources needed to do so successfully. General trust in leadership may not be sufficient on its own to change AI adoption intentions once perceived risk and social influence are considered. Leaders can build credibility through visible AI governance: clarifying how AI tools are monitored, how data are protected, how bias concerns are addressed, and who is accountable when AI contributes to errors. These concrete safeguards can indirectly support adoption by reducing employees' perceived risk, which emerged as a key inhibitor in this study.

This study has several limitations that should be considered when interpreting the findings. First, the outcome variable captured behavioral intention rather than actual AI use. While prior research indicates a strong correlation between intention and actual use (Venkatesh et al., 2003), intentions may not always translate to actual use. Second, the use of Prolific to recruit respondents based in the United States only may represent a heterogenous set of organization and industries. This may impact generalizability to other countries, industries and settings maybe limited particularly for organization level constructs like organizational trust. Third, the model focused on social influence, organizational trust, perceived risks while other core technology adoption determinants, including the other UTAUT constructs (Venkatesh et al., 2003), were not modeled which may explain additional variance in AI adoption intentions. Fourth, the conceptualization of AI. In this research, AI was presented to respondents as a general technological concept rather than a specific type, application or system. As a result, respondents may have interpreted AI differently depending on their background and technology familiarity. These differences in AI interpretation may influence their perceptions of risk, trust and social influence associated with AI adoption. Consequently, the results of this research should be interpreted within the boundary condition that they reflect the employees' general perceptions AI adoption rather than perceptions towards a specific type of AI or technology.

Recommendations for Future Research

As this study advances understanding of workplace AI adoption, several opportunities for future research remain. First, scholars should refine the theoretical model by re-specifying organizational trust (OT). Given OT's non-significance as a direct predictor and moderator in this study, future models should test whether OT operates indirectly by reducing perceived risk (OT → PR → BI) and whether AI-specific trust, for example, trust in AI outputs, data stewardship, or AI governance, better explains adoption intentions than general organizational trust. Second, because role was the only significant control variable, future research should examine role-based differences more explicitly to determine whether the effects of perceived risk, social influence, and their interaction vary across job levels or decision authority. Third, considering the mixed item-level predictive performance, future studies should further decompose the perceived risk construct by comparing models that treat risk as a higher-order factor with models that examine risk dimensions separately (e.g., performance, privacy, psychological, and time risk) to identify which concerns most strongly inhibit adoption. Finally, because the present study is cross-sectional, longitudinal or experimental designs are needed to strengthen causal inference and to assess how risk perceptions, social influence, and trust evolve as AI becomes embedded in routine organizational work.

Conclusion

This study set out to investigate employees' behavioral intention for artificial intelligence adoption in organizational settings by testing the direct effects of perceived risks, organizational trust, and social influence on adoption intentions. The study also investigated the moderating roles of social influence and organizational trust on the relationship between perceived risks and behavioral intention to adopt AI. Data were collected and analyzed using SmartPLS version 4, utilizing the partial least squares structural equation modeling (PLS-SEM) technique. The analyzed dataset, acquired through a survey of diverse respondents working in United States based companies, indicated that perceived risk has a negative significant relationship with the employees' behavioral intention for AI adoption. This means, perceived risk acts as one of the barriers hindering optimum adoption of AI in organizations. The results reveal that as employees' risk perceptions increase, their intention to adopt artificial intelligence decreases reinforcing the importance of proper change management that addresses fears and uncertainty during the process of artificial intelligence adoption.

Consistent with existing literature (Venkatesh et al., 2003), the results from this study indicate that social influence is positively and significantly associated with behavioral intention to adopt artificial intelligence. In addition, the interaction effect between social influence and perceived risk was also statistically significant, implying that social influence attenuates the negative association between perceived risk and behavioral intention. These findings suggest that organizations can improve AI adoption outcomes by deliberately fostering supporting workplace norms. When respected peers speak positively about artificial intelligence and supervisors visibly endorse and model the use of AI, employees' risk concerns are reduced and intention to adopt increases through social influence. Leaders should identify and empower peer champions and continuously publicize practical success stories and use cases, that all employees can internalize positive adoption norms increasing confidence in the technology and reducing individual risk aversion.

In contrast, organizational trust did not demonstrate any significant direct or moderating effects in this model, indicating that the influence of trust may be more conditional, may operate through indirect mechanisms like shaping perceived risk, or may require more AI-specific trust conceptualizations to be detected in models specific for AI adoption intention.

Overall, the structural model explained a substantial proportion of variance in behavioral intention to adopt artificial intelligence with an $R^2 = 0.439$ and demonstrated a strong predictive relevance with a $Q^2 = 0.411$. Practically, these findings suggest that organizations seeking to realize the benefits of artificial intelligence technology should prioritize strategies that reduce perceived risks, including targeted communication, training, and governance practices, while shaping the social narrative around AI in the company by leveraging credible peer champions and visible support for successful, positive, and responsible use cases. Finally, the non-significant effects of organizational trust point to important opportunities for future research to refine trust measurement and model specification, particularly in ways that capture trust in artificial intelligence use in organizations.

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APPENDIX A: SUMMARY OF SURVEY CONSTRUCTS AND ITEMS

Construct / Variable	Number of Items	Source
Initial Qualification Questions	3	Developed for this study
Demographic Information	7	Developed for this study
Behavioral Intention to Adopt AI	3	Venkatesh et al., 2003
Perceived Risk		
Performance Risk	5	Featherman & Pavlou (2003)
Privacy Risk	3	Featherman & Pavlou (2003)
Psychological Risk	2	Featherman & Pavlou (2003)
Time Risk	4	Featherman & Pavlou (2003)
Overall Risk	5	Featherman & Pavlou (2003)
Social Influence	7	Mathiesen (1991); Thompson et al. (1991); Moore and Benbasat (1991)
Organizational Trust		
Ability / Competence	6	Mayer & Davis (1999)
Benevolence	5	Mayer & Davis (1999)
Integrity	5	Mayer & Davis (1999)

APPENDIX B: SURVEY CONSTRUCTS AND ITEMS

Construct	Items
Perceived Risk (Featherman & Pavlou, 2003)	***Performance Risk***
	1. The AI system might not perform well and could cause problems for me.
	2. The security mechanisms built into the AI system may not be sufficient to protect my information or account.
	3. There is a significant likelihood that the AI system may not function as intended or may malfunction frequently.
	4. Considering the expected performance of the AI system, using it would be risky for me.
	5. The AI system may not perform reliably and could produce incorrect outcomes or errors.
	Privacy Risk
	1. There is a chance that using the AI system will cause me to lose control over my personal data or private information.
	2. Signing up for and using the AI system could lead to a loss of privacy, as my personal information might be used or shared without my consent.
	3. Cybercriminals might gain unauthorized access to my personal data if I use this AI system.
	Psychological Risk
	1. Using the AI system does not align well with my self-image or personal values.
	2. Adopting this AI system could lead to a feeling of psychological discomfort or conflict because it doesn't fit my self-concept.
	Time Risk
	1. If I adopt the AI system, there is a chance I might lose valuable time if I have to switch later to an alternative solution.
	2. Adopting and using this AI system might cause inconvenience because I may waste significant time resolving errors or problems.
	3. Considering the time investment required to learn and integrate the AI system makes adopting it risky.
	4. The potential time loss involved in configuring and learning how to effectively use the AI system makes it less attractive.
	Overall Risk
	1. Overall, considering all relevant factors, adopting this AI system would be risky.
	2. I consider adopting and using this AI system to be inherently risky.
	3. Using this AI system is potentially dangerous.

	4. Adopting this AI system would introduce significant uncertainty into my activities.
	5. Overall, using this AI system exposes me to substantial risks.
Social Influence (Mathiesen, 1991; Thompson et al., 1991; Moore & Benbasat, 1991)	***Subjective Norm*** (Mathiesen, 1991)
	1. People who influence my behavior think that I should use Artificial Intelligence
	2. People who are important to me think I should use Artificial Intelligence
	Social Factors (Thompson et al., 1991)
	1. I will use Artificial Intelligence because of the proportion of coworkers who use AI
	2. My immediate supervisor is very supportive of the use of AI for my job
	Image (Moore & Benbasat, 1991)
	1. People in my organization who use AI have more prestige than those who do not.
	2. People in my organization who use AI have a high profile
	3. Having or using AI is a status symbol in my organization
Organizational Trust (Mayer & Davis, 1999)	***Ability / Competence***
	1. Top management is very capable of performing its job
	2. Top management is known to be successful at the things it tries to do
	3. Top management has much knowledge about the work that needs done
	4. I feel very confident about top management's skills
	5. Top management has specialized capabilities that can increase our performance
	6. Top management is well qualified
	Benevolence
	1. Top management is very concerned about my welfare
	2. My needs and desires are very important to top management
	3. Top management would not knowingly do anything to hurt me
	4. Top management really looks out for what is important to me
	5. Top management will go out of its way to help me
	Integrity
	1. Top management has a strong sense of justice
	2. I never have to wonder whether top management will stick to its word
	3. Top management tries hard to be fair in dealings with others
	4. I like top management's values
	5. Sound principles seem to guide top management's behavior
Behavioral Intention (Venkatesh et al., 2003)	1. I intend to use Artificial Intelligence (AI) in my work
	2. I predict I will use Artificial Intelligence (AI) in my work
	3. I plan to use Artificial Intelligence (AI) in of my work

APPENDIX C: SURVEY FOR DATA COLLECTION

UNC Charlotte, Belk College of Business

Name of the Investigators(s):

Primary Investigator: Michael Musau
Faculty Advisor: Dr. Reginald Silver

Request to participate in research.

We would like to invite you to take part in a research project. The purpose of this research is to ascertain understanding, perceptions, and concerns around the intention to adopt and use of Artificial Intelligence Technology. The participation is completely OPTIONAL.

You must be at least 18 years old to be in this research project.
You must reside and work in the United States.
You must be employed in a U.S. based firm.

If you choose to participate, you will complete an online survey that takes approximately **10–15 minutes**. The survey will ask questions about your perceptions and experiences related to AI adoption in a professional setting.

The survey will also include demographic questions, including, age, gender, role/position, and tenure. You may choose not to answer any question

There are no foreseeable risks or discomforts to you for taking part in this study

This study is administered through Prolific. If you complete the survey as instructed, you will receive a monetary compensation as defined in your agreement with Prolific. Completion means (1) you reach the end of the survey and submit your responses, and (2) you return to Prolific and enter a valid completion code.

How the payment works: After completing and submitting the survey, you will receive a completion code. You must enter this code into Prolific to submit your response. Once your submission is approved in Prolific, compensation is issued through Prolific according to its process. Participants who complete the survey receive the full study reward shown in Prolific. Participants who are ended early, either due to eligibility confirmation or quality checks) will receive the minimum payment for their time, as described in Prolific.

You will NOT receive the full study reward if:

- You do not complete the survey (including exiting before submitting the survey).

- You do not enter a valid completion code (or provide an invalid code) when submitting through Prolific.

 Your responses to the eligibility confirmation questions indicate you are not eligible, and the survey ends early (minimum payment applies).

 You do not correctly answer the attention-check questions included to ensure data quality, and the survey ends early (minimum payment applies).

Your participation in this study will be handled in a confidential manner. Any reports publications based on this research will use only group data and will not identify you or any individual as being of this project. After this study is complete, study data may be shared with other researchers for use in other studies without asking for your consent again. The data we share will NOT include information that could identify you.

Consent to Participate
Your decision to participate in this research is entirely up to you. Participation is voluntary, and you may choose not to respond or participate in this study. You may stop participating and withdraw from the survey at any time; however, if you withdraw or do not submit the survey, you will not receive the Prolific participation payment and the study team will not save or utilize any of your data in this study, the data will be deleted**.** There are no other penalties or consequences for choosing not to participate or for withdrawing. By starting the survey or submitting the completed survey, you are indicating your informed consent to participate in this study. Thank you for your time and thoughtful contribution to this research project. If you have any questions about this study, please contact:

Michael Musau mmusau@uncc.edu or
Dr Reginald Silver rsilver5@uncc.edu

If you have any questions about your rights in this research, you may contact the office of research protections and integrity at uncc-irb@uncc.edu

Survey Questions:

Q1. Are you currently employed (either full-time or part-time)? N / Y

Q2. Do you actively use Artificial Intelligence (AI) at your workplace? N / Y

Q3. Does your company / place of employment intend to start using Artificial Intelligence (AI)?

- My company / place of employment currently users AI
- My company / place of employment has plans to use AI within the next 6 months
- My company / place of employment has plans to use AI within the next 12 months (1 Year)
- My company / place of employment has plans to use AI after 12 months (more than 1 Year from now)
- My company / place of employment has NO plans in place when to start using AI

Q4. How long have you been employed at your current organization (in years)?

Q5. What Industry do you work in?

- Banking / Finance
- Education
- Government / Public Service
- Health Care
- Hospitality / travel
- Manufacturing
- Media / Entertainment
- Professional Services
- Retail / Consumer Goods
- Technology / IT
- Other

Q6. Which of the following best describes your current role or position within your organization?

- o Entry-level
- o Individual Contributor / Professional / Specialist
- o Manager / Team Lead
- o Senior Manager / Department Head
- o Executive or C-level (e.g., CEO, CTO, VP)

Q7. How many years of total professional work experience do you have?

Q8. What is your age (in years)?

Q9. What is your gender identity?

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

All other items below are on a 7-point Likert scale.

1 = Strongly disagree | 2 = Disagree | 3 = Somewhat Disagree | 4 = Neither agree nor disagree | 5 = Somewhat agree | 6 = Agree | 7 = Strongly agree

Perceived Risk

Q10. The AI system might not perform well and could cause problems for me.

Q11. The security mechanisms built into the AI system may not be sufficient to protect my information or account.

Q12. There is a significant likelihood that the AI system may not function as intended or may malfunction frequently.

Q13. Considering the expected performance of the AI system, using it would be risky for me.

Q14. The AI system may not perform reliably and could produce incorrect outcomes or errors.

Q15. There is a chance that using the AI system will cause me to lose control over my personal data or private information.

Q16. Signing up for and using the AI system could lead to a loss of privacy, as my personal information might be used or shared without my consent.

Q17. Cybercriminals might gain unauthorized access to my personal data if I use this AI system.

Q18. This question is to check attention: Please select “Neither agree nor disagree” for this statement.

Q19. Using the AI system does not align well with my self-image or personal values.

Q20. Adopting this AI system could lead to a feeling of psychological discomfort or conflict because it doesn't fit my self-concept.

Q21. If I adopt the AI system, there is a chance I might lose valuable time if I have to switch later to an alternative solution.

Q22. Adopting and using this AI system might cause inconvenience because I may waste significant time resolving errors or problems.

Q23. Considering the time investment required to learn and integrate the AI system makes adopting it risky.

Q24. The potential time loss involved in configuring and learning how to effectively use the AI system makes it less attractive.

Q25. Overall, considering all relevant factors, adopting this AI system would be risky.

Q26. I consider adopting and using this AI system to be inherently risky.

Q27. Using this AI system is potentially dangerous.

Q28. Adopting this AI system would introduce significant uncertainty into my activities.

Q29. Overall, using this AI system exposes me to substantial risks.

Social Influence

Q30. People who influence my behavior think that I should use Artificial Intelligence

Q31. People who are important to me think I should use Artificial Intelligence

Q32. I will use Artificial Intelligence because of the proportion of coworkers who use AI

Q33. My immediate supervisor is very supportive of the use of AI for my job

Q34. People in my organization who use AI have more prestige than those who do not.

Q35. People in my organization who use AI have a high profile

Q36. Having or using AI is a status symbol in my organization

Q37. I have never heard of the internet, computers, or technology.

Organization Trust

Q38. Top management is very capable of performing its job

Q39. Top management is known to be successful at the things it tries to do

Q40. Top management has much knowledge about the work that needs done

Q41. I feel very confident about top management's skills

Q42. Top management has specialized capabilities that can increase our performance

Q43. Top management is well qualified

Q44. Top management is very concerned about my welfare

Q45. My needs and desires are very important to top management

Q46. Top management would not knowingly do anything to hurt me

Q47. Top management really looks out for what is important to me

Q48. Top management will go out of its way to help me

Q49. Top management has a strong sense of justice

Q50. I never have to wonder whether top management will stick to its word

Q51. Top management tries hard to be fair in dealings with others

Q52. I like top management's values

Q53. Sound principles seem to guide top management's behavior

Q54. As an attention check, please select "Strongly Agree" for this question.

Behavioral Intention to Adopt AI

Q55. I intend to use Artificial Intelligence (AI) in my work

Q56. I predict I will use Artificial Intelligence (AI) in my work

Q57. I plan to use Artificial Intelligence (AI) in of my work

Conclusion

Thank you for taking the time to complete this survey, your participation is greatly appreciated and will contribute meaningfully to advancing our understanding of AI adoption in the workplace. Please be assured that all responses will remain anonymous and strictly confidential. The data collected will be used solely for academic research purposes.