Artificial Intelligence Readiness Scale: Extending Model for Enterprise AI Adoption

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Abstract

This dissertation develops and validates the AI Readiness Scale (AIRS), an instrument designed to measure artificial intelligence adoption readiness. Extending the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with AI-specific constructs, this study examines factors influencing behavioral intention to adopt AI tools among students and employed professionals.

Using a sample of 523 United States professionals and students, exploratory and confirmatory factor analyses validated an 8-factor, 16-item model demonstrating excellent fit (CFI = .975, TLI = .960, RMSEA = .065). The structural model revealed Price Value (β = .505, p < .001), Hedonic Motivation (β = .217, p = .014), and Social Influence (β = .136, p = .024) as significant predictors of behavioral intention, while AI Trust approached but did not reach significance (β = .106, p = .064).

Four theoretically-proposed constructs (Voluntariness, Explainability, Ethical Risk, AI Anxiety) were excluded due to inadequate reliability (α = .30–.58), revealing measurement challenges with two-item scales for multi-dimensional AI constructs. Notably, traditional UTAUT predictors including Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Habit did not significantly predict AI adoption intention, suggesting AI tools may represent a distinct technology category where cost-benefit perceptions and enjoyment outweigh conventional utility considerations.

The study contributes a psychometrically validated instrument for AI adoption research and identifies practical implications for organizational AI implementation strategies. Findings suggest that demonstrating value relative to cost (Price Value) and fostering positive engagement experiences (Hedonic Motivation) represent the most impactful intervention targets for promoting AI adoption in higher education settings.

Keywords: artificial intelligence, technology adoption, UTAUT2, scale development, higher education, AI readiness, psychometric validation, structural equation modeling

Contents

Chapter 1: Introduction

1.1 Background and Context

Artificial intelligence (AI) has evolved from a specialist capability to a foundational driver of enterprise transformation. Between 2023 and 2025, organizations accelerated AI integration across functions and geographies, fueled by advances in large language models, cloud-based ecosystems, and rapid democratization through enterprise platforms such as Microsoft 365 Copilot and ChatGPT Enterprise.

According to McKinsey's *State of AI* series, AI adoption has accelerated dramatically: after hovering around 50 percent for years, adoption jumped to 72 percent in 2024 and reached 88 percent by late 2025 (McKinsey & Company, 2024, 2025). This growth represents a fundamental shift in how organizations approach technology—AI is no longer an experimental capability but an expected component of modern work.

Yet this growth in adoption has not translated proportionally into business impact. Boston Consulting Group reported that only 5 percent of companies achieve measurable business value from AI initiatives, while roughly 74 percent struggle to scale beyond proofs of concept (Boston Consulting Group, 2024, 2025). McKinsey found that only about 6 percent of organizations qualify as "AI high performers"—those attributing meaningful EBIT impact to AI and reporting significant value—while most organizations remain in piloting rather than scaling phases (McKinsey & Company, 2025). IBM's Global AI Adoption Index found that 37 percent of enterprises cite data complexity and quality as their top barrier to AI success (IBM, 2023), while Capgemini reports that companies embedding AI into redesigned workflows achieve 1.7 times higher ROI than those merely layering AI atop legacy processes (Capgemini Research Institute, 2025).

These figures reveal a paradox: AI is nearly ubiquitous, yet most enterprises fail to realize sustained economic or operational returns. MIT Media Lab's NANDA initiative estimates that 90 to 95 percent of generative-AI pilots fail to scale or yield measurable profit-and-loss improvements (MIT Media Lab, 2025). This persistent gap between adoption rates and value realization—termed

the "adoption-value gap"—represents both a significant business challenge and a research opportunity.

Understanding why individuals adopt or resist AI tools is essential for closing this gap. While organizational-level barriers such as data infrastructure, governance frameworks, and change management have received considerable attention in practitioner literature, individual-level adoption psychology remains underexplored in empirical research. Technology acceptance research offers theoretical frameworks for understanding these individual differences, yet existing instruments were developed for earlier technology generations and may not capture the unique characteristics of AI tools.

1.2 Statement of the Problem

Despite decades of technology acceptance research, organizations lack validated instruments for assessing individual-level AI adoption readiness. This gap creates three interconnected problems:

Theoretical Gap: The dominant technology acceptance framework—the Unified Theory of Acceptance and Use of Technology 2 (UTAUT2)—was developed and validated primarily on mobile and consumer technologies (Venkatesh et al., 2012a). While UTAUT2 explains significant variance in technology adoption generally, AI tools present unique characteristics that may require theoretical extension. These include concerns about job displacement, questions of algorithmic transparency, and trust in autonomous decision-making systems. Venkatesh (2021) identified nine unique research challenges for AI adoption that existing frameworks do not fully address, calling for empirical investigation of AI-specific adoption factors.

Measurement Gap: Current AI adoption assessments in organizational practice rely largely on ad hoc surveys or general technology readiness measures. No psychometrically validated instrument exists specifically for measuring AI adoption readiness in professional and academic contexts. This measurement gap limits both research comparability and practical diagnostic utility.

Practice Gap: Organizations invest heavily in AI infrastructure and training but often lack the diagnostic tools to identify which employees are likely to adopt AI tools, which will resist, and why. Without valid measurement instruments, intervention strategies remain poorly targeted. The 90–95 percent pilot failure rate suggests that technology deployment without attention to individual adoption psychology produces limited returns (MIT Media Lab, 2025). Deloitte reports that 60 percent of enterprises lack sufficient AI expertise for operational integration (Deloitte, 2024), while Gartner finds that more than 40 percent of AI projects face delay or cancellation due to unclear governance (Gartner, 2025).

1.3 Purpose of the Study

The purpose of this study is to develop and validate the **AI Readiness Scale (AIRS)**—a psychometrically sound instrument extending UTAUT2 for enterprise AI tool adoption. Specifically, this research aims to:

1. **Develop** a theoretically grounded measurement instrument incorporating both established UTAUT2 constructs and AI-specific factors, particularly AI Trust.

2. **Validate** the instrument through rigorous split-sample methodology, using exploratory factor analysis (EFA) on a development sample and confirmatory factor analysis (CFA) on an independent holdout sample.

3. **Test** structural relationships between adoption predictors and behavioral intention through structural equation modeling (SEM).

4. **Examine** measurement invariance across student and professional populations to establish the instrument's applicability across diverse workforce contexts.

5. **Identify** moderating factors—including professional experience and AI usage frequency— that influence adoption pathways.

6. **Provide** organizations with a validated diagnostic tool for assessing workforce AI readiness and targeting adoption interventions.

1.4 Research Questions and Hypotheses

1.4.1 Research Questions

Primary Research Question: How can UTAUT2 be extended with AI-specific constructs to better predict behavioral intention to adopt AI tools in professional and academic contexts?

Secondary Research Questions:

1. What is the factor structure of an AI-specific adoption readiness instrument?
2. Does the instrument demonstrate measurement invariance across student and professional populations?
3. Which factors most strongly predict behavioral intention to adopt AI tools?
4. Does AI Trust significantly predict adoption intention beyond UTAUT2 constructs?
5. What moderating factors influence the relationships between predictors and adoption intention?

1.4.2 Research Hypotheses

Based on UTAUT2 theory and AI-specific considerations, this study tests the following hypotheses:

Core UTAUT2 Hypotheses (H1a–H1g): - H1a–H1g: The seven UTAUT2 constructs (Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, Price Value, and Habit) positively predict Behavioral Intention to adopt AI tools.

AI Extension Hypothesis (H2): - H2: AI Trust positively predicts Behavioral Intention beyond UTAUT2 constructs.

Moderation Hypotheses (H3–H4): - H3: Professional experience moderates the relationships between predictors and Behavioral Intention. - H4: Population (Student vs. Professional) moderates the relationships between predictors and Behavioral Intention.

Behavioral Validation Hypothesis (H5): - H5: Behavioral Intention positively correlates with actual AI tool usage behavior.

Full hypothesis specifications with theoretical rationales are presented in Chapter 3 §3.3.2.

1.5 Theoretical and Practical Significance

1.5.1 Theoretical Significance

This study makes several contributions to technology acceptance scholarship:

Framework Extension: By empirically testing AI-specific constructs alongside established UTAUT2 predictors, this research extends technology acceptance theory to the AI domain. The theoretical extension responds to Venkatesh's (2021) call for AI-specific adoption research and addresses the unique characteristics of AI technologies that distinguish them from previous technology generations.

Construct Validation: The development of reliable measures for AI Trust provides validated operationalizations for future research. The psychometric validation process—including convergent validity, discriminant validity, and composite reliability assessment—ensures that these constructs meet scholarly standards for measurement quality.

Cross-Population Invariance: Testing measurement invariance across student and professional populations advances understanding of how adoption factors function across diverse workforce contexts. Configural invariance findings support the instrument's utility for comparative research across population segments.

Moderation Discovery: Identification of experience as a moderating factor on hedonic motivation pathways contributes novel insights to the technology acceptance literature, suggesting that adoption mechanisms may differ based on user characteristics in ways not previously documented.

1.5.2 Practical Significance

Beyond theoretical contributions, this research provides actionable tools and insights for organizations:

Diagnostic Instrument: The validated 16-item AIRS provides organizations with a practical tool for assessing workforce AI readiness. The instrument's brevity (approximately 5 minutes to complete) enables deployment at scale while maintaining psychometric rigor.

Intervention Targeting: The four-segment user typology identified through cluster analysis—AI Enthusiasts (16%), Cautious Adopters (30%), Moderate Users (37%), and Anxious Avoiders (17%)—provides actionable categories for targeted intervention design. Each segment requires different change management approaches.

Evidence-Based Messaging: The finding that Price Value (β = .505) dominates adoption intention—rather than traditional performance messaging—suggests organizations should emphasize cost-benefit value propositions in AI adoption communications.

Experience-Tailored Training: The moderating effect of professional experience on hedonic motivation pathways indicates that experienced professionals may require different engagement strategies than early-career employees.

1.6 Scope and Delimitations

1.6.1 Scope

This study focuses on individual-level adoption of AI tools in professional and academic contexts. The research:

- **Examines** behavioral intention to adopt AI tools as the primary outcome variable, with actual tool usage as a behavioral validation criterion.
- **Encompasses** both students and employed professionals across multiple industries, providing cross-population generalizability testing.
- **Includes** common AI tools such as ChatGPT, Microsoft Copilot, and Google Gemini as the technology context.
- **Applies** established psychometric validation methodology including split-sample EFA/CFA, structural equation modeling, and measurement invariance testing.

- **Addresses** adoption predictors at the individual psychological level rather than organiza-
  tional or technological levels.

1.6.2 Delimitations

The following boundaries define what this study does not address:

Organizational Factors: While organizational infrastructure undoubtedly influences AI adoption, this study focuses on individual-level psychological predictors rather than organizational readiness factors such as IT infrastructure, leadership support, or governance frameworks.

Actual Behavior Prediction: The primary outcome is behavioral intention rather than sustained behavioral change. While intention strongly correlates with self-reported usage (ρ = .69), the study does not track actual usage behavior over time.

Specific AI Tool Comparison: The study examines AI tool adoption generally rather than comparing adoption patterns across specific tools (e.g., ChatGPT vs. Copilot).

Cultural Context: Data collection occurred in a single national context (primarily United States respondents). Cross-cultural generalizability requires future investigation.

Dropped Constructs: Four initially proposed AI-specific constructs—Voluntariness (α = .406), Explainability (α = .582), Ethical Risk (α = .546), and AI Anxiety (α = .301)—demonstrated inadequate reliability and were excluded from the validated model. These constructs remain theoretically important but require revised operationalization in future research.

1.7 Definition of Key Terms

Term	Definition
UTAUT2	Unified Theory of Acceptance and Use of Technology 2 (Venkatesh et al., 2012)
AIRS	AI Readiness Scale—the 16-item psychometric instrument developed and validated in this study
AI Trust	Confidence in AI systems' reliability, accuracy, and benevolence; a novel construct extending UTAUT2 for AI-specific adoption contexts

Term	Definition
Behavioral Intention	An individual's stated intention to use AI tools in their professional or academic work
Performance Expectancy	The degree to which using AI tools is expected to enhance job performance
Effort Expectancy	The perceived ease of use associated with AI tools
Social Influence	The degree to which important others believe one should use AI tools
Facilitating Conditions	Perceptions of organizational and technical infrastructure supporting AI use
Hedonic Motivation	The fun or pleasure derived from using AI tools
Price Value	The cognitive trade-off between perceived benefits of AI tools and their monetary cost
AI Anxiety	Apprehension or fear associated with AI technology
Measurement Invariance	The extent to which a measurement instrument functions equivalently across different groups

1.8 Summary and Dissertation Structure

This chapter has introduced the research problem, purpose, questions, and significance of this study examining AI adoption readiness in professional and academic contexts.

The dissertation is organized into six chapters:

Chapter 1: Introduction establishes the research context, problem statement, research questions, and significance of the study.

Chapter 2: Literature Review examines the evolution of technology acceptance models from TAM through UTAUT2, synthesizes AI-specific adoption research, and develops the conceptual framework for the study.

Chapter 3: Research Methodology describes the research design, sampling procedures, instrument development, and analytical strategy employed in the ten-phase validation approach.

Chapter 4: Findings presents the empirical results from exploratory factor analysis, confirmatory factor analysis, measurement invariance testing, structural equation modeling, and behavioral validation.

Chapter 5: Analysis and Discussion interprets the findings in relation to existing literature, discusses theoretical and practical implications, and addresses unexpected findings.

Chapter 6: Conclusions, Implications, and Recommendations summarizes the study's contributions, provides recommendations for practitioners and organizations, acknowledges limitations, and suggests directions for future research.

Chapter 2: Literature Review

2.1 Introduction

The rapid enterprise adoption of artificial intelligence has outpaced the explanatory capacity of traditional technology acceptance frameworks. While organizations have embraced AI at unprecedented rates—rising from approximately 50% historically to 72% in 2024 and 88% by late 2025 (McKinsey & Company, 2024, 2025)—most remain in piloting phases rather than scaled deployment. McKinsey reports that only about one-third of organizations have begun scaling AI programs, and just 6% qualify as "AI high performers" with meaningful enterprise-level EBIT impact (McKinsey & Company, 2025). This adoption-value paradox presents both a theoretical puzzle and a practical challenge: why do established technology acceptance models incompletely predict AI adoption, and what additional constructs must be incorporated to guide organizational intervention?

This chapter establishes the theoretical foundation for the Artificial Intelligence Readiness Scale (AIRS) by pursuing three objectives. First, it traces the evolution of technology acceptance research from foundational behavioral theories through the Unified Theory of Acceptance and Use of Technology (UTAUT) and its consumer extension (UTAUT2), establishing the empirical baseline that informs scale development. Second, it examines why AI—as a socio-technical phenomenon characterized by opacity, probabilistic reasoning, and ethical exposure—stresses this baseline in ways that demand construct extension. Third, it synthesizes emerging research on AI-specific determinants of adoption, including trust, anxiety, and explainability, to justify the theoretical framework and hypotheses tested in subsequent chapters.

The review draws on three categories of evidence. Academic research provides the theoretical architecture, anchored by Venkatesh et al.'s (2003, 2012) foundational UTAUT work, Blut et al.'s (2022) comprehensive meta-analysis spanning 737,112 users across 1,935 independent samples, and Venkatesh's (2021) AI-specific research agenda. Industry benchmarks from McKinsey, Boston Consulting Group, and MIT Media Lab contextualize these theoretical insights within the

current enterprise AI landscape. Finally, empirical studies on AI trust, explainability, and anxiety provide construct-level evidence for the proposed extensions.

This dual-lens approach—integrating academic rigor with business relevance—reflects the Doctor of Business Administration orientation of this thesis. The literature review not only establishes scholarly grounding but also identifies practical implications: why AI adoption programs fail, what organizational levers matter, and how validated measurement can inform change management. By the chapter's conclusion, readers will understand why AIRS extends UTAUT2 with AI-specific constructs and how the resulting framework addresses both theoretical gaps and practitioner needs.

2.2 Technology Acceptance Models: Foundations and Evolution

2.2.1 Early Behavioral Theories

The study of technology adoption originates in broader behavioral science. Ajzen's (1991) Theory of Planned Behavior (TPB) explains volitional behavior through three determinants: attitudes toward the behavior, subjective norms reflecting perceived social pressure, and perceived behavioral control representing self-efficacy and resource availability. TPB's parsimony and empirical generalizability made it adaptable to early information systems research, yet it remains technology-agnostic—it does not model perceptions unique to digital systems such as usefulness or ease of use.

Davis's (1989) Technology Acceptance Model (TAM) addressed this limitation by introducing two technology-specific beliefs: perceived usefulness (the degree to which a user believes technology will enhance job performance) and perceived ease of use (the degree to which technology use is free of effort). TAM's elegant specification and consistent empirical support established it as the dominant paradigm in information systems research for over two decades. However, TAM's parsimony becomes a limitation when technologies carry salient ethical, organizational, or epistemic properties that instrumental beliefs alone cannot capture.

Rogers's (2003) Diffusion of Innovations theory complements these individual-level models by explaining how innovations spread through social systems over time. Five innovation

attributes—relative advantage, compatibility, complexity, trialability, and observability—predict adoption rates across populations. While diffusion theory illuminates organizational uptake and social influence, it is less diagnostic for the psychological mechanisms underlying individual decisions to rely on complex, partially opaque systems such as modern AI.

2.2.2 The Unified Theory of Acceptance and Use of Technology (UTAUT)

Venkatesh et al. (2003) synthesized eight prominent acceptance models into the Unified Theory of Acceptance and Use of Technology (UTAUT), achieving superior explanatory power through theoretical integration. UTAUT specifies four direct determinants of behavioral intention and use:

Performance Expectancy (PE) captures the degree to which using technology will help attain job performance gains, integrating perceived usefulness (TAM), extrinsic motivation, job-fit, relative advantage, and outcome expectations from prior theories.

Effort Expectancy (EE) represents the ease associated with technology use, incorporating perceived ease of use (TAM), complexity (innovation diffusion), and ease of use from other frameworks.

Social Influence (SI) reflects the degree to which important others believe the individual should use the technology, synthesizing subjective norm, social factors, and image constructs.

Facilitating Conditions (FC) captures organizational and technical infrastructure supporting use, including perceived behavioral control, facilitating conditions, and compatibility from prior models.

UTAUT further specifies four moderators—gender, age, experience, and voluntariness—that systematically alter the strength of predictor-intention relationships. In the original validation, UTAUT explained 70% of variance in behavioral intention, substantially exceeding the explanatory power of its constituent theories.

2.2.3 Meta-Analytic Evidence: The Current State of UTAUT

Blut et al.'s (2022) landmark meta-analysis provides the most comprehensive assessment of UTAUT to date, synthesizing 25,619 effect sizes from 737,112 users across 1,935 independent samples. This analysis not only confirms UTAUT's core predictions but also reveals nuanced patterns essential for AI-context extensions.

Performance Expectancy emerges as the consistently strongest predictor of behavioral intention, with a meta-analytic correlation of $\rho = .60$ and substantial effect sizes across contexts. This finding aligns with decades of TAM research positioning perceived usefulness as the primary adoption driver and has direct implications for AI messaging strategies in organizations.

Effort Expectancy shows moderate effects ($\rho = .45$) but displays greater context-dependency. In established technology categories where interfaces have matured, effort expectancy may reach ceiling effects—users assume baseline usability. This pattern suggests that for contemporary AI tools with polished interfaces, ease-of-use investments may show diminishing returns relative to other adoption levers.

Social Influence demonstrates inconsistent effects across organizational versus consumer contexts, with stronger impact under mandatory use conditions. Facilitating Conditions shows a direct effect on use behavior that strengthens with experience, suggesting infrastructure and support matter more for sustained engagement than initial adoption.

Critically, Blut et al. (2022) identify substantial unexplained variance and call for domain-specific extensions that incorporate constructs relevant to emerging technologies. They observe that the "red ocean" of UTAUT research has produced diminishing theoretical returns, yet faithful application with appropriate extensions remains productive. This finding directly motivates the present study's AI-specific extensions.

2.2.4 UTAUT2: Consumer Context Extensions
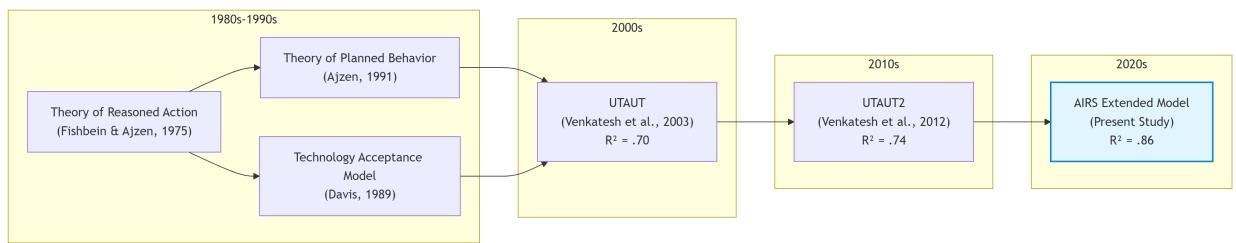
Venkatesh et al. (2012) extended UTAUT for consumer contexts through UTAUT2, adding three constructs:

Hedonic Motivation (HM) captures fun or pleasure derived from technology use, acknowledging that consumer adoption is driven by intrinsic enjoyment alongside instrumental outcomes.

Price Value (PV) represents the cognitive trade-off between perceived benefits and monetary cost, relevant when users bear technology expenses directly.

Habit (HB) reflects automaticity developed through prior behavior, acknowledging that repeated use becomes self-reinforcing independent of conscious intention.

UTAUT2 explained 74% of variance in behavioral intention, demonstrating the value of context-appropriate extensions. For the present research, UTAUT2 provides the baseline framework, with modifications appropriate to workplace AI contexts where hedonic motivation and habit remain relevant while price value may be less salient (organizational rather than personal expenditure).

2.3 The AI Adoption-Value Gap: Industry Context

2.3.1 Current State of Enterprise AI Adoption

Before examining why traditional acceptance models require extension for AI, it is essential to understand the practical landscape these models must explain. Industry benchmarks reveal a striking paradox: AI adoption has reached near-ubiquity, yet value realization remains exceptional.

According to McKinsey's State of AI series, organizational AI adoption jumped from approximately 50% (where it had hovered for years) to 72% in 2024, and further increased to 88%

by late 2025 (McKinsey & Company, 2024, 2025). This acceleration, driven primarily by generative AI capabilities and accessible enterprise platforms, represents one of the fastest technology adoption curves in organizational history.

Yet adoption has not translated into proportional value capture. Boston Consulting Group reports that only 5% of companies achieve measurable business value from AI initiatives, while approximately 74% struggle to scale beyond proofs of concept (Boston Consulting Group, 2024, 2025). McKinsey finds that only about 6% of organizations qualify as "AI high performers"—those attributing 5% or more of EBIT to AI use and reporting significant value—while just 39% report any enterprise-level EBIT impact (McKinsey & Company, 2025). IBM's Global AI Adoption Index found that 42% of enterprise-scale organizations had deployed AI with another 40% actively piloting solutions, yet 37% cite data complexity as their top barrier (IBM, 2023).

The MIT Media Lab's NANDA Initiative provides perhaps the most sobering assessment: 90–95% of generative AI pilots fail to scale or deliver measurable profit-and-loss improvements (MIT Media Lab, 2025). Georgian's AI Benchmark 2025 corroborates this pattern, finding that only 32% of enterprises had deployed AI across multiple business functions (Georgian & NewtonX, 2025). This failure rate exceeds typical technology project failures, suggesting AI-specific barriers that traditional change management and technology deployment frameworks do not adequately address.

2.3.2 Diagnosing the Gap: Why Adoption Does Not Equal Value

Industry analyses converge on three systemic barriers underlying the adoption-value gap:

Scaling Failure: Most organizations can demonstrate AI feasibility in controlled pilots but lack the operational design, governance architecture, and change infrastructure to move innovations into production. Georgian's AI Benchmark 2025 found that only 32% of enterprises had deployed AI across multiple business functions (Georgian & NewtonX, 2025), while ISG's State of Enterprise AI Adoption report confirms that scaling remains the top challenge across industries (Information Services Group, 2025). These findings indicate that organizational rather than tech-

nological constraints limit scaling.

Governance and Trust Deficits: Organizations struggle with ownership, compliance, bias mitigation, and ethical use policies. The gap between AI deployment speed and governance framework development creates risk exposure that prudent organizations constrain through limited adoption scope. McKinsey finds that AI high performers are three times more likely than their peers to have senior leaders who demonstrate strong ownership and commitment to AI initiatives (McKinsey & Company, 2025). Gartner identifies governance maturity as a primary differentiator between AI leaders and laggards, noting that more than 40% of AI projects face delay or cancellation due to unclear governance (Gartner, 2025).

Capability and Change Barriers: Misalignment across functions, skill gaps, and resistance to workflow redesign inhibit AI integration. Deloitte reports that 60% of enterprises lack sufficient AI or machine learning expertise for operational integration (Deloitte, 2024), while Lucidworks finds that organizations with company-wide AI literacy programs achieve faster adoption and stronger employee trust (Lucidworks, 2025). Capgemini reports that organizations embedding AI into redesigned workflows achieve 1.7 times higher ROI than those layering AI onto legacy processes (Capgemini Research Institute, 2025), yet such redesign requires capabilities and change tolerance that most organizations lack.

2.3.3 Implications for Acceptance Research

This industry context has direct implications for technology acceptance research. The adoption-value gap suggests that traditional acceptance constructs—useful for predicting initial adoption intention—may incompletely explain the sustained, consequential use that generates organizational value. If 88% of organizations have adopted AI while only 6% achieve meaningful EBIT impact, then factors beyond performance and effort expectancy must mediate the translation from adoption to value.

Venkatesh (2021) argues that AI tools present unique adoption challenges that existing frameworks do not fully address. Unlike prior technologies, AI systems (1) operate as partially

opaque decision aids where underlying models are "blackboxed"; (2) make errors that accumulate and erode trust over time; (3) require learning periods during which performance improves; (4) may develop emergent biases unknown at deployment; and (5) shift the human role from decision-maker to decision-overseer or decision-recipient. These characteristics suggest that trust, transparency, and anxiety—constructs largely peripheral in traditional acceptance models—move to the foreground for AI adoption.

2.4 Why AI Stresses Traditional Acceptance Models

2.4.1 Opacity and Explainability

Many AI systems, particularly those employing deep learning, function as partially opaque decision aids. Users—and often developers—cannot fully articulate why a model produces specific outputs. This characteristic fundamentally challenges traditional acceptance models, which assume users can form reasoned judgments about technology usefulness based on observable performance.

Venkatesh (2021) identifies model opacity as a primary barrier to AI adoption: when users have "little or no visibility into the underlying algorithm or process that renders the decision," they cannot calibrate trust or develop the performance expectations that drive adoption in transparent systems. Doshi-Velez and Kim (2017) argue that interpretability and explainability become central to justified reliance when systems are opaque and consequential.

The construct of **perceived explainability**—whether users can understand and utilize reasons behind AI outputs with sufficient clarity to justify action—emerges from this limitation. Shin (2021) distinguishes explainability from causability (the user's ability to infer cause-effect logic adequate for decision-making), demonstrating that higher perceived explainability increases both trust and intention to use. Critically, explainability effects extend beyond system perceptions to trust in the human teams responsible for deployment and oversight, indicating organizational implications beyond individual acceptance.

2.4.2 Probabilistic Behavior and Model Errors

AI systems operate probabilistically, producing outputs that are correct in expectation but not guaranteed for individual cases. This characteristic distinguishes AI from deterministic software where identical inputs yield identical outputs. Venkatesh (2021) notes that "almost by definition, a model is bound to make mistakes, given that it is, after all, a representation of reality."

For adoption, this probabilistic nature creates a trust challenge. Users must accept that errors will occur while maintaining sufficient confidence to rely on outputs for consequential decisions. Traditional acceptance models do not explicitly address this calibrated-trust requirement. The UTAUT construct of performance expectancy assumes users can assess technology usefulness; probabilistic AI requires users to assess expected utility across a distribution of possible outcomes, some of which will be incorrect.

Furthermore, AI models learn over time, meaning initial performance may not predict mature performance. Users who experience early errors may form negative performance expectations that persist even as systems improve—a dynamic traditional acceptance models do not capture.

2.4.3 Ethical Exposure and Accountability

AI introduces distinctive ethical exposures around bias, privacy, and accountability that shape willingness to rely on outputs. The widely-publicized case of Amazon's AI hiring tool— which systematically discriminated against women job applicants—illustrates how AI systems can encode and amplify biases present in training data (Schuetz & Venkatesh, 2020).

Floridi et al. (2018) articulate an ethical framework identifying AI-specific risks: autonomy erosion, privacy invasion, unfair discrimination, and accountability gaps. These risks generate **perceived ethical risk**—anticipated harms that depress adoption intention even when performance expectations are favorable. Dwivedi et al. (2021) demonstrate that perceived ethical risk exerts direct negative effects on intention and moderates the influence of traditional predictors like performance expectancy and social influence.

In enterprise contexts, ethical risk connects to organizational legitimacy and governance. Users assess not only whether AI works but whether reliance is appropriate given fairness, privacy, and accountability implications. When organizations fail to establish clear governance—bias audits, escalation pathways, human-in-the-loop procedures—users may limit consequential reliance regardless of system capability.

2.4.4 Autonomy and Human Role Transformation

AI's autonomy capabilities fundamentally alter the human role in work processes. Traditional decision support technologies augment human judgment; AI can supplant it. Venkatesh (2021) observes that "with AI tools, the human decision maker—i.e., employee—could thus be relegated to playing a secondary role or have no role to play."

This transformation generates **AI-related anxiety**—affective responses to autonomy, opacity, and rapid change. Unlike technology anxiety rooted in difficulty of use, AI anxiety encompasses concerns about job displacement, loss of professional agency, and erosion of human expertise. Tao et al. (2020) conceptualize AI anxiety through multiple dimensions including privacy-related anxiety, bias-related anxiety, and opacity-related anxiety. Kim et al. (2025) add anticipatory anxiety about future disruptions and existential concerns about human obsolescence.

Research suggests anxiety may exhibit nonlinear relationships with exposure. Moderate, calibrated exposure can reduce anxiety as users develop realistic expectations and coping strategies, while minimal exposure leaves fears unchallenged and intensive exposure may overwhelm adaptive capacity (Frenkenberg & Hochman, 2025). This pattern implies that training and hands-on experience can shift affective responses favorably—an organizational lever absent from traditional acceptance frameworks.

2.5 Trust in AI Systems

2.5.1 Conceptualizing AI Trust

Trust has emerged as a gateway condition for AI adoption—without sufficient trust, users hesitate to rely on outputs even when systems appear useful. Langer et al.'s (2023) comprehensive review of empirical research on trust in AI positions trust as mediating the relationship between system properties and behavioral outcomes across application areas.

AI trust adapts the ability-integrity-benevolence triad from interpersonal trust research to algorithmic agents (Siau & Wang, 2018). **Ability** translates to perceived AI competence and accuracy; **integrity** becomes perceptions of fairness and consistency; **benevolence** maps to alignment between AI outputs and user or organizational goals. Stevens and Stetson (2023) operationalize these facets in the Trust and Acceptance of AI Technology (TrAAIT) scale, demonstrating that multi-dimensional trust can be measured reliably in professional settings.

2.5.2 Trust as Mediator and Amplifier

Empirical evidence positions trust as both a direct predictor of adoption intention and a mechanism through which other factors operate. When trust is high, performance expectancy shows stronger effects on intention—users translate positive system evaluations into adoption when they trust the system to perform consistently. When trust is low, even objectively capable systems fail to generate adoption intention because users doubt whether observed performance will generalize to their consequential decisions.
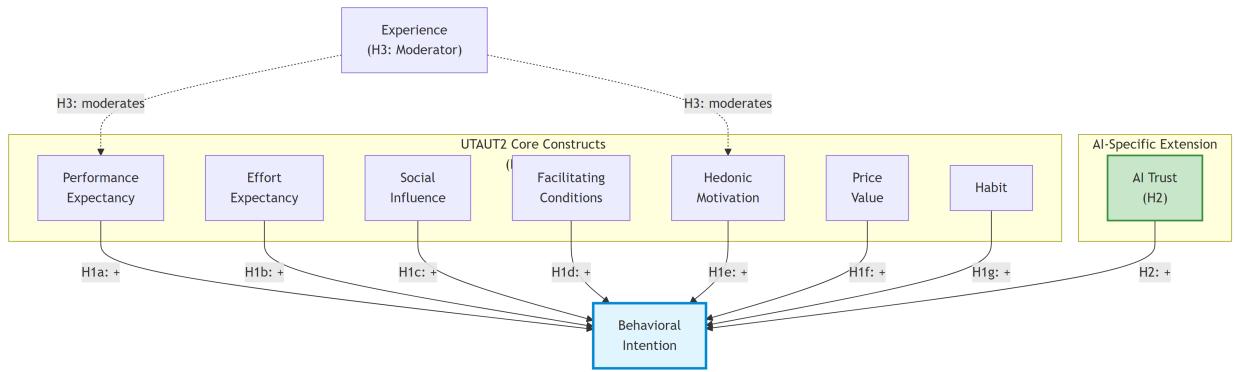
Explainability serves as a primary antecedent of trust. Shin (2021) demonstrates that when users perceive AI explanations as clear, sufficient, and actionable, trust increases. This explainability-to-trust pathway provides an organizational lever: investing in explanation design can build trust without altering underlying AI capability.

Governance practices also shape trust. When organizations establish bias audits, privacy safeguards, and clear accountability structures, perceived ethical risk decreases and trust increases.

Stevens and Stetson (2023) find that trust in the people and processes behind AI deployment contributes to system trust, suggesting that organizational governance operates through trust to influence adoption.

2.5.3 Trust in the Present Research

Given the empirical evidence for trust's central role in AI adoption, the present research incorporates **AI Trust** as a core construct extending UTAUT2. AI Trust is operationalized as confidence that the AI system is reliable, competent, and aligned with user and organizational values. This construct is expected to positively predict behavioral intention directly and to mediate effects of explainability and governance perceptions on intention.

Note: AI Anxiety was initially proposed as an inhibitor construct (H8) but was excluded from the final model due to inadequate reliability ($\alpha = .30$). See Chapter 4 for details.

2.6 AI-Related Anxiety

2.6.1 Conceptualizing AI Anxiety

AI-related anxiety captures affective responses to AI autonomy, opacity, and the pace of technological change. Unlike general technology anxiety rooted in difficulty of use, AI anxiety encompasses broader concerns about human obsolescence, loss of agency, and unpredictable societal transformation.

Tao et al. (2020) developed a multi-dimensional AI anxiety scale identifying distinct facets: anxiety about AI learning and communication, AI social influence, AI configuration, and AI devel-

opment trajectory. Frenkenberg and Hochman (2025) add anticipatory dimensions, distinguishing anxiety about current AI from anxiety about future AI capabilities. Kim et al. (2025) identify annihilation anxiety—existential concerns about human relevance—as a component particularly salient among knowledge workers whose expertise AI may replicate.

2.6.2 Anxiety as Inhibitor

Anxiety operates as an inhibitor in adoption models, exerting direct negative effects on intention and potentially attenuating the positive influence of performance expectancy and other drivers. Users experiencing high AI anxiety may acknowledge system usefulness while remaining unwilling to rely on AI for consequential decisions.

Importantly, anxiety effects may be nonlinear with exposure. Several studies observe that moderate, structured exposure to AI reduces anxiety by replacing vague fears with realistic expectations and coping strategies. This suggests that enablement programs and hands-on training can shift anxiety levels favorably—an organizational intervention that traditional acceptance models do not explicitly accommodate.

2.6.3 Anxiety in the Present Research

The present research incorporates **AI Anxiety** as an inhibitor construct extending UTAUT2. AI Anxiety is operationalized as affective unease about AI autonomy, opacity, and potential negative consequences. This construct is expected to negatively predict behavioral intention and may moderate the effects of positive predictors, particularly for users with limited AI experience.

2.7 Gaps in Current Research

The literature review reveals several gaps that the present research addresses:

Gap 1: Validated AI-Specific Measurement Instruments. While theoretical arguments for AI-specific constructs are well-developed, validated measurement instruments remain scarce. Most existing AI adoption studies adapt general technology acceptance measures or develop ad hoc

items without rigorous scale development. The present research addresses this gap through systematic scale development following established psychometric procedures (Hinkin, 1998; DeVellis, 2017).

Gap 2: Integration of Enablers and Inhibitors. Prior research tends to study AI-specific constructs in isolation. Few studies simultaneously model trust and anxiety as enabler and inhibitor within an integrated UTAUT2 framework. The present research tests an integrative model where AI Trust operates as an enabler and AI Anxiety as an inhibitor alongside traditional UTAUT2 predictors.

Gap 3: Cross-Population Validation. Most AI adoption studies examine single populations, limiting generalizability claims. Whether adoption dynamics differ between student and professional populations—groups with potentially different AI exposure, organizational contexts, and role relationships—remains unexamined. The present research addresses this gap through multigroup analysis across student and professional samples.

Gap 4: Experience as Moderator. While UTAUT specifies experience as a moderator of traditional predictors, the moderating role of AI experience on AI-specific constructs is unexplored. Given theoretical arguments that anxiety decreases with calibrated exposure, experience moderation is particularly relevant for AI adoption. The present research tests experience moderation across both traditional and AI-specific paths.

Gap 5: Connection to Practitioner Concerns. Academic research on AI adoption often proceeds disconnected from practitioner challenges. The adoption-value gap identified in industry benchmarks reflects organizational barriers—governance, change management, workforce readiness—that acceptance research rarely addresses directly. The present research bridges this gap by developing a diagnostic instrument (AIRS) with explicit organizational applications.

2.8 Theoretical Framework and Hypotheses

2.8.1 Conceptual Model

The present research proposes an extended UTAUT2 model for AI adoption that retains the validated core while adding AI-specific enabler and inhibitor constructs. The model specifies:

UTAUT2 Core Predictors: Performance Expectancy, Effort Expectancy, Social Influence, Facilitating Conditions, Hedonic Motivation, and Habit as direct predictors of Behavioral Intention. Price Value is omitted given the organizational (rather than personal purchase) context.

AI-Specific Extension: AI Trust as an enabler positively predicting Behavioral Intention, and AI Anxiety as an inhibitor negatively predicting Behavioral Intention.

Moderation: AI experience moderating predictor-intention relationships, with theoretical expectations that experience strengthens performance expectancy effects and weakens anxiety effects.

2.8.2 Core UTAUT2 Hypotheses

Based on the meta-analytic evidence reviewed above, the following hypotheses reflect established UTAUT2 relationships:

H1a (Performance Expectancy): Performance Expectancy positively predicts Behavioral Intention to use AI tools.

Rationale: Blut et al.'s (2022) meta-analysis confirms performance expectancy as the consistently strongest predictor ($\rho = .60$). Users who believe AI will enhance their job performance should demonstrate greater adoption intention.

H1b (Effort Expectancy): Effort Expectancy positively predicts Behavioral Intention to use AI tools.

Rationale: While meta-analytic effects are moderate and context-dependent, perceived ease of use remains a relevant consideration, particularly for users with limited AI experience.

H1c (Social Influence): Social Influence positively predicts Behavioral Intention to use AI

tools.

Rationale: Perceptions that important others endorse AI use should increase adoption intention, particularly in organizational contexts where peer and supervisor expectations are salient.

H1d (Facilitating Conditions): Facilitating Conditions positively predicts Behavioral Intention to use AI tools.

Rationale: Organizational infrastructure, training, and support should enable adoption by reducing barriers and signaling organizational commitment.

H1e (Hedonic Motivation): Hedonic Motivation positively predicts Behavioral Intention to use AI tools.

Rationale: Users who experience pleasure and enjoyment from AI interaction should demonstrate greater adoption intention, consistent with UTAUT2 findings in consumer contexts.

H1f (Price Value): Price Value positively predicts Behavioral Intention to use AI tools.

Rationale: Users who perceive favorable cost-benefit tradeoffs for AI tools should demonstrate greater adoption intention, particularly where personal or organizational investment is visible.

H1g (Habit): Habit positively predicts Behavioral Intention to use AI tools.

Rationale: Established patterns of AI use should predict continued intention through automaticity and reinforcement mechanisms.

2.8.3 AI-Specific Extension Hypotheses

H2 (AI Trust): AI Trust positively predicts Behavioral Intention to use AI tools beyond UTAUT2 core constructs.

Rationale: Building on Langer et al.'s (2023) review and Stevens and Stetson's (2023) validation work, trust serves as a gateway condition for AI adoption. Users who trust AI systems to be reliable, competent, and aligned with their interests should demonstrate greater adoption intention.

Proposed Inhibitor (AI Anxiety): AI Anxiety was hypothesized to negatively predict Behavioral Intention to use AI tools. However, empirical analysis revealed inadequate reliability for the AI Anxiety scale ($\alpha = .30$), preventing formal hypothesis testing. This measurement challenge

with anxiety constructs is discussed in Chapter 4 and Chapter 5.

Theoretical Rationale: Drawing on Tao et al. (2020), Kim et al. (2025), and Frenkenberg and Hochman (2025), anxiety about AI autonomy, opacity, and consequences should inhibit adoption intention even when other perceptions are favorable. Future research with improved anxiety measurement is recommended.

2.8.4 Moderation Hypotheses

H3 (Experience Moderation): Experience moderates the relationships between predictors and Behavioral Intention, such that:

- (a) The effect of Performance Expectancy on Intention strengthens with greater AI experience

- (b) The effect of Hedonic Motivation on Intention strengthens with greater AI experience

Rationale: Experienced users can more accurately assess AI performance and may derive greater enjoyment from sophisticated use.

H4 (Role Group Moderation): Role group (Academic vs. Professional+Leader) moderates UTAUT2 path coefficients.

Rationale: Students and working professionals operate in different organizational contexts with distinct resource availability, social pressure patterns, and technology access, which may differentially affect adoption determinants.
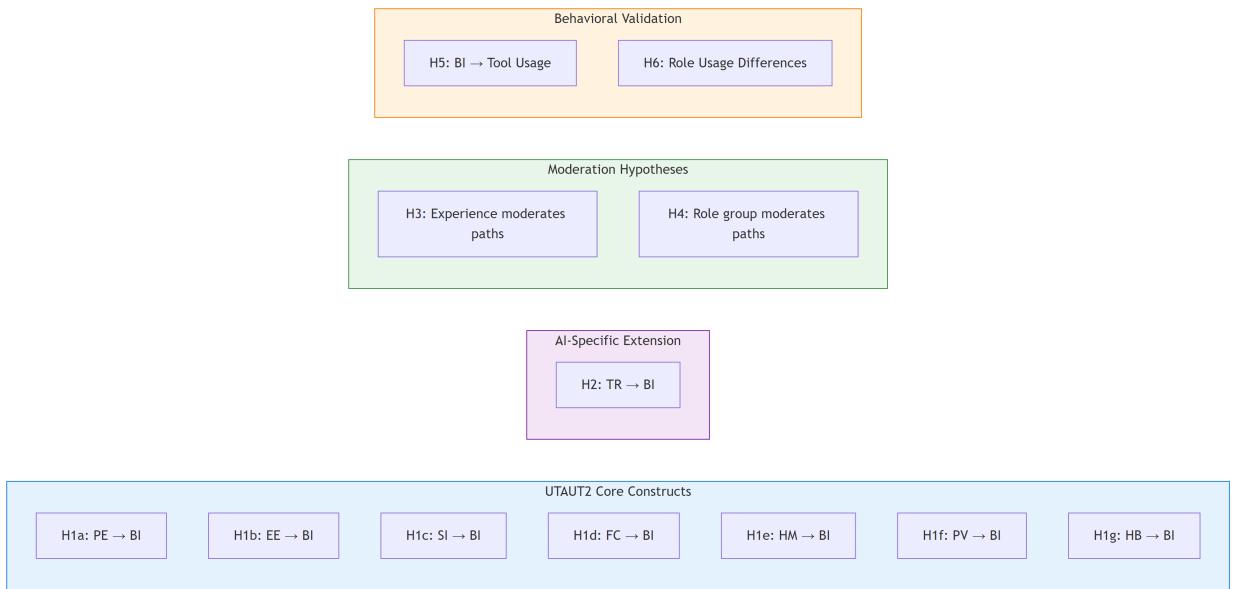
2.8.5 Behavioral Validation Hypotheses

H5 (Behavioral Intention → Usage): Behavioral Intention positively relates to actual AI tool usage breadth.

Rationale: Consistent with UTAUT theory, intention should translate to behavior. Higher adoption intention should correspond to greater engagement with AI tools.

H6 (Role Group Usage Differences): Role groups differ significantly in AI tool usage patterns.

Rationale: Professionals with greater workplace technology demands and resources may exhibit different AI tool usage patterns than students.

2.9 Chapter Summary

This chapter established the theoretical foundation for the Artificial Intelligence Readiness Scale through four contributions.

First, it traced the evolution of technology acceptance research from foundational theories through UTAUT and UTAUT2, emphasizing Blut et al.'s (2022) meta-analytic confirmation of performance expectancy as the strongest adoption predictor while identifying substantial unexplained variance that invites domain-specific extension.

Second, it contextualized the theoretical discussion within the contemporary AI adoption-value gap, using industry benchmarks to demonstrate that traditional acceptance frameworks incompletely explain why 76% organizational adoption yields only 5% value realization. This gap motivates investigation of factors beyond traditional constructs.

Third, it examined AI's distinctive characteristics—opacity, probabilistic behavior, ethical exposure, and human role transformation—that stress traditional acceptance models. These characteristics justify the incorporation of AI Trust as an enabler and AI Anxiety as an inhibitor within an extended UTAUT2 framework.

Fourth, it articulated the research hypotheses tested in subsequent chapters, specifying both traditional UTAUT2 relationships and AI-specific extensions with experience moderation.

The theoretical framework positions AIRS as a principled extension that respects the durability of established acceptance research while acknowledging AI's socio-technical distinctives. The resulting instrument should provide both scholarly contribution—validated measurement of AI-specific adoption determinants—and a foundation for future practical applications in organizational AI readiness assessment.

The following chapter describes the methodology employed to develop and validate the AIRS instrument, including sample composition, measurement procedures, and analytic approach.

Chapter 3: Research Methodology

3.1 Introduction

This chapter describes the research methodology employed to develop and validate the AI Readiness Scale (AIRS) and test the extended UTAUT model for AI tool adoption in higher education. The study follows established scale development procedures (DeVellis & Thorpe, 2021; Hinkin, 1998) combined with structural equation modeling to examine relationships between latent constructs. The research design prioritizes psychometric rigor through split-sample cross-validation, comprehensive validity assessment, and multi-group invariance testing.

The chapter is organized as follows: Section 3.2 describes the research philosophy and design; Section 3.3 details the theoretical framework and hypotheses; Section 3.4 covers instrument development; Section 3.5 addresses sampling and data collection; Section 3.6 presents the analytical strategy; Section 3.7 discusses reliability and validity; Section 3.8 covers ethical considerations; and Section 3.9 acknowledges methodological limitations.

3.2 Research Design

3.2.1 Research Philosophy

This study adopts a **post-positivist** philosophical stance, recognizing that while objective reality exists, our understanding of it is necessarily imperfect and probabilistic (Creswell & Creswell, 2018). This orientation is appropriate for scale development research, which seeks to measure latent psychological constructs through observable indicators while acknowledging measurement error and the provisional nature of theoretical models.

The post-positivist approach manifests in several methodological choices:

- Emphasis on **replication and cross-validation** through split-sample design
- Use of **probabilistic inference** (confidence intervals, effect sizes) rather than binary significance testing

- Recognition of **measurement error** through latent variable modeling
- **Theory-driven** hypothesis testing with openness to unexpected findings

3.2.2 Research Approach

The study employs a **sequential mixed methods design** (Creswell & Clark, 2017) with quantitative primacy:

1. **Primary Quantitative Component**: Structured survey measuring UTAUT constructs on Likert scales, analyzed through factor analysis and structural equation modeling

2. **Supplementary Qualitative Component**: Open-ended feedback questions analyzed through thematic analysis to provide contextual depth and identify emergent themes not captured by closed-ended items

This design allows triangulation of findings, with qualitative data enriching interpretation of quantitative patterns (e.g., understanding why certain constructs predict adoption more strongly than others).

3.2.3 Time Horizon

The study employs a **cross-sectional design** with data collected during November 2024. While cross-sectional designs preclude causal inference, they are standard for initial scale validation studies (DeVellis & Thorpe, 2021). The design captures a snapshot of AI adoption readiness during a period of rapid AI tool proliferation in higher education, providing a baseline for future longitudinal research.

3.2.4 Research Context

The study was conducted with **United States professionals and students**, encompassing:

- Full-time and part-time students (undergraduate and postgraduate)

- Employed professionals (individual contributors, managers, executives)

- Freelancers and self-employed individuals

Students are included because they are transitioning into an AI-infused job market and will soon make adoption decisions inside organizations; their readiness is therefore directly relevant to near-term enterprise contexts (proposal §7.2). This context was selected for theoretical and practical relevance: knowledge-intensive work settings where AI tools have significant potential impact on productivity, yet adoption patterns remain poorly understood.

3.3 Theoretical Framework and Hypotheses

3.3.1 Extended UTAUT Model

The study extends Venkatesh et al.'s (2012) Unified Theory of Acceptance and Use of Technology 2 (UTAUT2) with AI-specific constructs. The theoretical model comprises eight latent factors predicting Behavioral Intention to adopt AI tools:

Core UTAUT2 Constructs:

- **Performance Expectancy (PE)**: The degree to which using AI tools will provide benefits in performing activities

- **Effort Expectancy (EE)**: The degree of ease associated with using AI tools

- **Social Influence (SI)**: The degree to which important others believe one should use AI tools

- **Facilitating Conditions (FC)**: Perceptions of resources and support available for AI tool use

- **Hedonic Motivation (HM)**: The fun or pleasure derived from using AI tools

AI-Specific Extensions:

- **Trust in AI (TR)**: Confidence in AI systems' reliability, accuracy, and benevolence

- **AI Anxiety (AX)**: Apprehension or fear associated with AI technology

Outcome:

- **Behavioral Intention (BI)**: Intent to adopt and use AI tools in professional/academic activities

3.3.2 Research Hypotheses

Based on UTAUT theory and emerging AI adoption literature, the following hypotheses were tested:

Primary Hypotheses (Direct Effects):

- H1a: Performance Expectancy positively predicts Behavioral Intention
- H1b: Effort Expectancy positively predicts Behavioral Intention
- H1c: Social Influence positively predicts Behavioral Intention
- H1d: Facilitating Conditions positively predicts Behavioral Intention
- H1e: Hedonic Motivation positively predicts Behavioral Intention
- H1f: Price Value positively predicts Behavioral Intention
- H1g: Habit positively predicts Behavioral Intention

AI-Specific Extension Hypothesis:

- H2: AI Trust positively predicts Behavioral Intention beyond UTAUT2 core constructs

Note: AI Anxiety (AX) was initially proposed as an inhibitor construct but was excluded from hypothesis testing due to inadequate reliability ($\alpha = .30$) identified during exploratory factor analysis. See Section 4.2 for construct development outcomes.

Moderation Hypotheses:

- H3: AI Experience moderates UTAUT relationships (strengthening effects for experienced users)
- H4: Role group (Student vs. Professional+Leader) moderates UTAUT path coefficients

Behavioral Validation:

- H5: Behavioral Intention positively relates to actual AI tool usage breadth
- H6: Role groups differ significantly in AI tool usage patterns

3.4 Instrument Development

3.4.1 Initial Item Pool

The initial AIRS instrument comprised **28 items across 12 constructs**:

- 7 core UTAUT2 constructs (14 items): PE, EE, SI, FC, HM, PV, HB
- 5 AI-specific extensions (10 items): TR, AX, VO, EX, ER
- 1 outcome construct (4 items): BI

Items were measured on 5-point Likert scales (1 = Strongly Disagree to 5 = Strongly Agree), with negatively-worded items (AX, ER) reverse-scored prior to analysis.

*Note: The final validated instrument comprises **16 items across 8 constructs** (PE, EE, SI, FC, HM, PV, HB, TR) plus the BI outcome. Four constructs (Voluntariness, Explainability, Ethical Risk, AI Anxiety) were excluded during EFA due to inadequate reliability (α = .30–.58). See Chapter 4, Section 4.2 for detailed item disposition.*

3.4.2 Item Sources

Items were adapted from established scales to ensure content validity:

Construct	Source	Adaptation
PE, EE, SI, FC, HM	Venkatesh et al. (2012) UTAUT2	Context adapted for AI tools
PV, HB	Venkatesh et al. (2012) UTAUT2	Context adapted for AI tools
TR	McKnight et al. (2002); Siau & Wang (2018)	Adapted for AI systems
AX	Venkatesh (2000); Meuter et al. (2003)	Technology anxiety → AI anxiety
VO	Moore & Benbasat (1991)	Voluntariness of use
EX	Shin (2021)	Explainability in AI
ER	Gursoy et al. (2019)	Ethical risk perception
BI	Venkatesh et al. (2003)	Standard UTAUT items

3.4.3 Content Validity

Content validity was established through:

1. **Literature Review**: Items grounded in established UTAUT and technology acceptance literature

2. **Construct Definition Mapping**: Each item mapped to specific construct definition

3. **Face Validity Review**: Items reviewed for clarity and appropriateness to AI context

3.4.4 Construct Exclusion Process

Of the 12 constructs proposed, **four AI-specific constructs were excluded** during exploratory factor analysis due to inadequate psychometric properties:

Construct	Items	Cronbach's α	Issue	Disposition
Voluntariness (VO)	VO1, VO2	.41	Multi-dimensional	Dropped
Explainability (EX)	EX1, EX2	.58	Multi-dimensional	Dropped
Ethical Risk (ER)	ER1, ER2	.55	Multi-dimensional	Dropped
AI Anxiety (AX)	AX1, AX2	.30	Item heterogeneity	Dropped

Interpretation: These constructs demonstrated poor inter-item correlations, suggesting the two-item scales measured different facets of multi-dimensional phenomena rather than unitary constructs. For example:

- **Voluntariness**: VO1 assessed choice to use AI, while VO2 assessed freedom not to use—conceptually distinct aspects of voluntary adoption

- **Explainability**: EX1 assessed understanding AI outputs, while EX2 assessed preference for explanations—comprehension vs. preference dimensions

- **Ethical Risk**: ER1 assessed job displacement concerns, while ER2 assessed privacy concerns—distinct risk categories

- **AI Anxiety**: AX1 captured technology avoidance, while AX2 captured fear of obsolescence—avoidance vs. approach motivations

Resolution: All four AI-specific constructs were excluded from the final measurement model due to inadequate reliability. These constructs remain theoretically important for AI adoption research and require more comprehensive operationalization with 3-4 items per sub-dimension in future studies.

Note: This represents an empirical finding, not a design limitation. The proposal committed to testing these constructs; the data revealed inadequate measurement properties. This transparent reporting aligns with best practices in scale development (DeVellis & Thorpe, 2021).

3.4.5 Final Instrument Structure

Following psychometric validation (see Chapter 4), the final AIRS instrument comprises **16 items across 8 factors** (7 UTAUT2 predictors + AI Trust extension):

Factor	Items	Example Item
Performance Expectancy	PE1, PE2	"Using AI tools increases my productivity"
Effort Expectancy	EE1, EE2	"Learning to use AI tools is easy for me"
Social Influence	SI1, SI2	"People important to me think I should use AI tools"
Facilitating Conditions	FC1, FC2	"I have the resources necessary to use AI tools"
Hedonic Motivation	HM1, HM2	"Using AI tools is fun"
Price Value	PV1, PV2	"AI tools are good value for the money"
Habit	HB1, HB2	"Using AI tools has become a habit for me"
AI Trust	TR1, TR2	"I trust AI tools to provide accurate information"

Note: Behavioral Intention (BI) serves as the outcome variable in the structural model.

3.5 Sampling and Data Collection

3.5.1 Target Population

The target population comprises adults in the United States who are either students or employed professionals (proposal §7.2). This includes:

- Full-time and part-time students at undergraduate and postgraduate levels

- Employed professionals in individual contributor roles

- Employed professionals in managerial and leadership roles

- Freelancers and self-employed individuals

3.5.2 Sampling Strategy

Convenience sampling was employed via:

- Institutional email distribution to staff and students

- Academic and professional network sharing

- Social media outreach (LinkedIn, Twitter/X)

While convenience sampling limits generalizability, it is appropriate for initial scale validation studies where the primary goal is psychometric evaluation rather than population inference (DeVellis & Thorpe, 2021).

3.5.3 Sample Size Determination

Target sample size was determined based on:

1. **SEM requirements**: Minimum N = 200 for stable Maximum Likelihood estimation (Kline, 2016)

2. **Factor analysis**: Minimum 10:1 subject-to-item ratio (Costello & Osborne, 2005)

3. **Multi-group analysis**: Minimum n = 100 per group (Hair et al., 2019)

4. **Split-sample cross-validation**: N > 500 to enable 50/50 split with adequate subsamples

   Achieved sample: N = 523 (exceeds all requirements)

3.5.4 Role Classification

Respondents were classified into three role groups based on self-reported primary role:

Category	Operational Definition	n	%
Student	Full-time students (n=196), part-time students (n=20)	216	41.3%
Professional	Individual contributors (n=112), freelancers (n=32), other (n=23), unemployed (n=17)	184	35.2%
Leader	Managers (n=71), executives (n=52)	123	23.5%

Note: For multi-group SEM requiring larger group sizes, Professional and Leader categories were combined (n = 307) to contrast with Student (n = 216). This grouping reflects meaningful theoretical distinctions between student-focused and employment-focused roles.

3.5.5 Data Collection Procedures

Platform: Qualtrics online survey platform

Collection Period: November 2024 (3-week window)

Procedures:

1. Participants accessed survey via distributed link

2. Informed consent obtained before data collection

3. Survey completion time: approximately 10-15 minutes

4. All responses anonymous; no personally identifiable information collected

3.5.6 Data Quality Assurance

Multiple quality checks were implemented:

Check	Criterion	Action
Completion status	Finished = True	Exclude incomplete responses
Response time	> 3 minutes	Exclude speeders
Attention checks	Correct response	Exclude inattentive responses
Pattern responding	Variance > 0	Exclude straight-line responses
Duplicate detection	Unique IP/device	Retain first response only
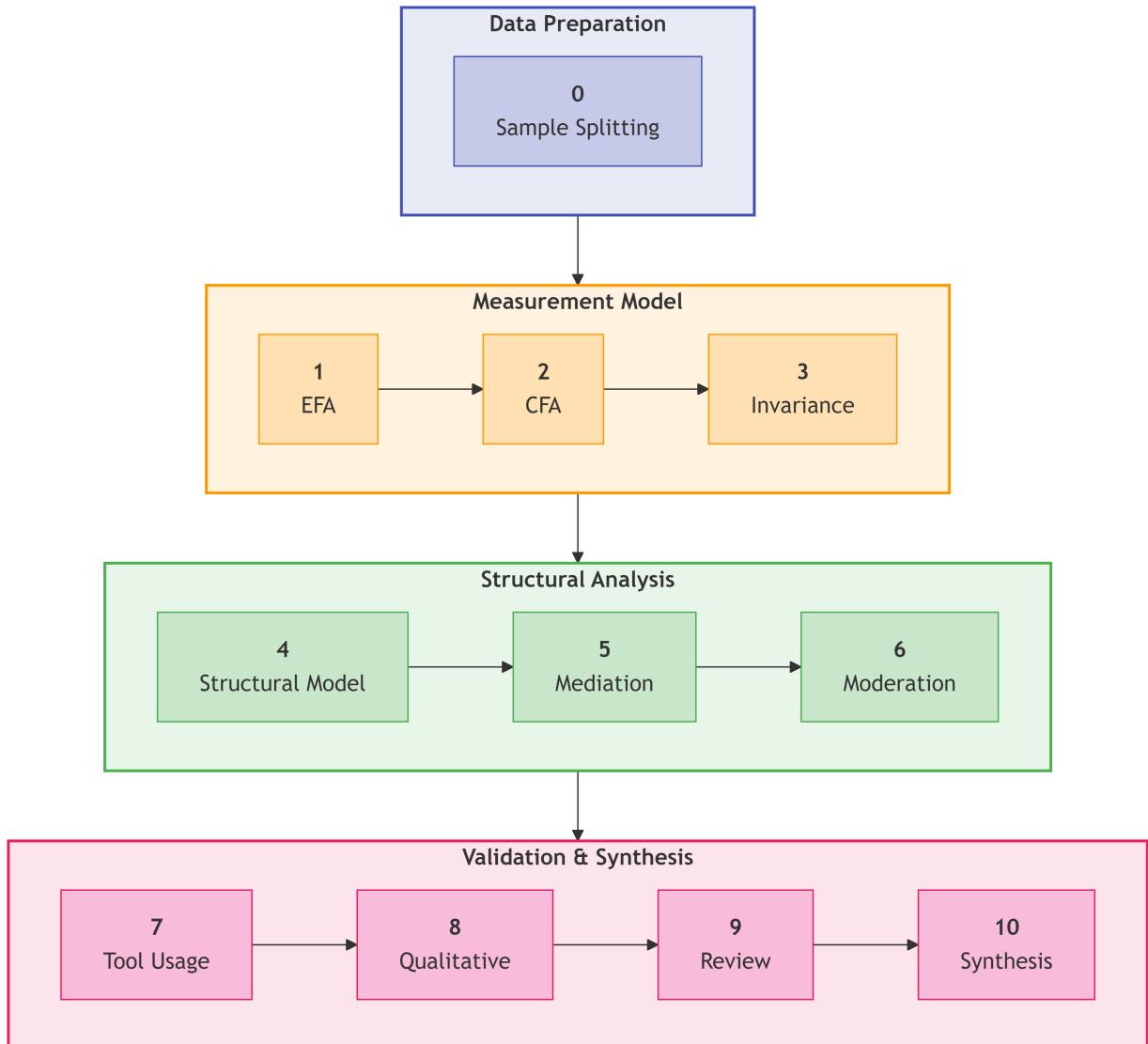
Final valid sample: N = 523 after quality screening

3.6 Analytical Strategy

3.6.1 Analysis Pipeline
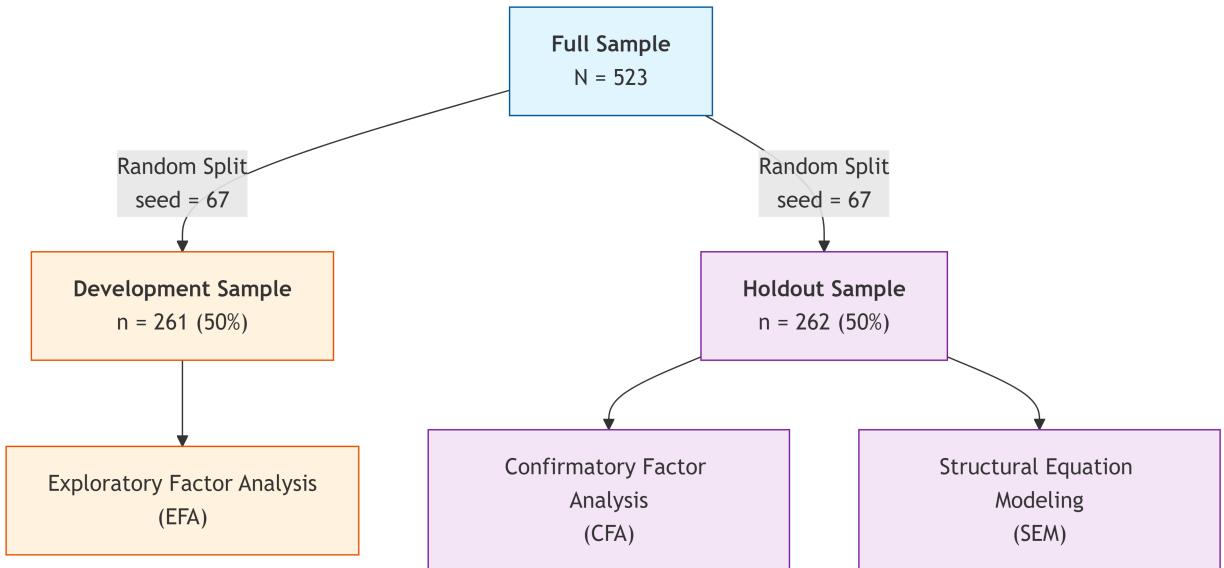
The analysis followed a systematic 10-phase pipeline ensuring replicability and transparency:

Phase	Notebook	Purpose
0	Sample Splitting	Create EFA/CFA subsamples
1	EFA	Explore factor structure
2	CFA	Validate factor structure
3	Invariance	Test measurement invariance
4	Structural Model	Test hypotheses
5	Mediation	Examine indirect effects
6	Moderation	Test moderating effects
7	Tool Usage	Behavioral validation
8	Qualitative	Thematic analysis
9	Comprehensive Review	Gap analysis
10	Final Synthesis	Integration

3.6.2 Sample Splitting Strategy

To ensure independent validation, the sample was randomly split:

Stratification: Split stratified by AI adoption status to ensure comparable samples

Reproducibility: Random seed (67) documented for exact replication

3.6.3 Exploratory Factor Analysis (EFA)

Purpose: Identify underlying factor structure and reduce item pool

Sample: Development subsample (n = 261)

Extraction Method: Principal Axis Factoring (PAF)

- Selected for robustness to non-normality
- Accounts for measurement error

Rotation: Promax (oblique)

- Allows correlated factors (theoretically appropriate)
- Pattern matrix used for interpretation

Factor Retention Criteria:

1. Kaiser criterion (eigenvalue > 1.0)
2. Parallel analysis (Horn, 1965)

3. Scree plot visual inspection

4. Theoretical interpretability

Item Retention Criteria:

Criterion	Threshold	Rationale
Primary loading	$\lambda \geq .50$	Strong factor association
Cross-loading	$\Delta\lambda \geq .20$	Simple structure
Communality	$h^2 \geq .30$	Adequate shared variance

Software: Python `factor_analyzer` package (v0.5.1)

3.6.4 Confirmatory Factor Analysis (CFA)

Purpose: Validate factor structure on independent sample

Sample: Holdout subsample (n = 262)

Estimation Method: Maximum Likelihood (ML)

- Standard for continuous indicators

- Provides χ^2 test and fit indices

Model Specification: 8-factor correlated model with 16 observed indicators (2 per factor)

Fit Index Thresholds:

Index	Acceptable	Good	Excellent
χ^2/df	< 5.0	< 3.0	< 2.0
CFI	$\geq .90$	$\geq .95$	$\geq .97$
TLI	$\geq .90$	$\geq .95$	$\geq .97$
RMSEA	$\leq .10$	$\leq .08$	$\leq .05$
SRMR	$\leq .10$	$\leq .08$	$\leq .05$

Thresholds based on Hu & Bentler (1999) and Hair et al. (2019).

Software: Python `semopy` package (v2.3.10)

3.6.5 Measurement Invariance Testing

Purpose: Establish construct comparability across role groups for valid multi-group comparison

Levels Tested:

Level	Constraint	Interpretation
Configural	Same factor structure	Qualitative equivalence
Metric	Equal factor loadings	Quantitative equivalence
Scalar	Equal intercepts	Mean comparability

Criteria for Invariance (Chen, 2007):
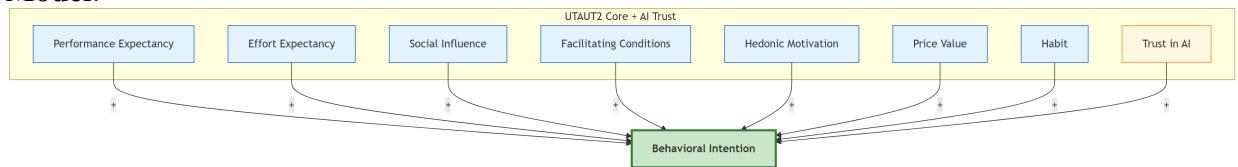
- ΔCFI < .010

- ΔRMSEA < .015

- $\Delta\chi^2$ non-significant (supplementary)

Groups: Student (n = 216) vs. Professional+Leader (n = 307)

3.6.6 Structural Equation Modeling (SEM)

Purpose: Test hypothesized relationships between latent constructs

Model:

Note: AI Anxiety was initially proposed but excluded due to inadequate reliability (α = .30).

Estimation: Maximum Likelihood with robust standard errors

Multi-Group Analysis: Separate models for Student and Professional+Leader groups

Moderation Testing:

- Experience × UTAUT interactions via latent interaction terms

- Role moderation via multi-group path comparison ($\Delta\chi^2$ tests)

Effect Size Interpretation (Cohen, 1988):

β	Interpretation
< .10	Negligible
.10–.29	Small
.30–.49	Medium
≥ .50	Large

3.6.7 Mediation Analysis

Purpose: Examine indirect pathways through the model

Method: Bootstrap estimation (1,000 resamples) for indirect effect confidence intervals

Significance: 95% CI excluding zero

3.6.8 Cluster Analysis

Purpose: Identify distinct user typologies based on UTAUT profile patterns

Method: K-means clustering

Variables: Standardized scores on 8 AIRS constructs

Cluster Selection:

- Elbow method

- Silhouette analysis

- Theoretical interpretability

Optimal Solution: $k = 4$ clusters

3.6.9 Qualitative Analysis

Purpose: Provide contextual depth and identify emergent themes

Data: Open-ended survey responses (n = 243 substantive responses, 46.5% response rate)

Method: Thematic analysis (Braun & Clarke, 2006)

1. Familiarization with data

2. Initial coding using keyword matching

3. Theme development and refinement

4. Theme prevalence quantification

5. Role-based comparison

Themes Identified: 10 distinct themes (see Chapter 4)

3.6.10 Statistical Software

All analyses conducted using Python 3.11 with the following packages:

Package	Version	Purpose
pandas	2.1.0	Data manipulation
numpy	1.26.0	Numerical computing
scipy	1.11.0	Statistical tests
factor_analyzer	0.5.1	Exploratory factor analysis
semopy	2.3.10	Confirmatory factor analysis, SEM
pingouin	0.5.3	Effect sizes, reliability
scikit-learn	1.3.0	Cluster analysis
matplotlib	3.8.0	Visualization
seaborn	0.13.0	Statistical graphics

Environment: Jupyter notebooks executed in VS Code with Python virtual environment

Reproducibility: All random operations use documented seeds; complete analysis pipeline available in GitHub repository

3.7 Reliability and Validity Assessment

3.7.1 Internal Consistency Reliability

Measures:

- **Cronbach's Alpha (α)**: Classical reliability coefficient

- **Composite Reliability (CR)**: SEM-based reliability accounting for differential loadings

Thresholds:

Measure	Minimum	Preferred
Cronbach's α	.70	.80
Composite Reliability	.70	.80

3.7.2 Convergent Validity

Definition: Extent to which indicators of a construct share variance

Assessment:

1. **Factor loadings**: All standardized loadings ≥ .70
2. **Average Variance Extracted (AVE)**: Proportion of variance captured by construct

   Threshold: AVE ≥ .50 (Fornell & Larcker, 1981)

3.7.3 Discriminant Validity

Definition: Extent to which constructs are distinct from one another

Assessment Methods:

1. **Fornell-Larcker Criterion**: √AVE > inter-construct correlations
2. **Heterotrait-Monotrait Ratio (HTMT)**: HTMT < .85 (Henseler et al., 2015)
3. **Maximum correlation**: |r| < .85 between any construct pair

3.7.4 Criterion Validity

Predictive Validity: AIRS constructs predict actual tool usage behavior ($\rho = .69$ for BI × tool breadth)

Known-Groups Validity: Constructs differentiate between theoretically-distinct groups (e.g., Leaders vs. Academics)

3.8 Ethical Considerations

3.8.1 Institutional Approval

The study received ethical approval from the institution's Research Ethics Committee prior to data collection. The research was classified as minimal risk given:

- Anonymous data collection

- Voluntary participation

- Non-sensitive topic

- Adult participants only

3.8.2 Informed Consent

Participants were provided with:

- Study purpose and objectives

- Data handling and storage procedures

- Right to withdraw without penalty

- Researcher contact information

Consent was obtained electronically before survey access. Participants could not proceed without acknowledging consent.

3.8.3 Anonymity and Confidentiality

Anonymity: No personally identifiable information collected

- No names, emails, or employee IDs

- IP addresses not recorded

- Demographic data collected at categorical level only

Confidentiality:

- Data stored on encrypted, password-protected systems

- Access limited to research team

- Data retained according to institutional policy (minimum 5 years)

3.8.4 Data Protection

The study complies with:

- IRB approval requirements

- Institutional data governance policies

- Research ethics standards for human subjects research

3.8.5 Participant Welfare

The survey addressed non-sensitive topics related to technology use attitudes. No anticipated risks to participant welfare. Contact information provided for questions or concerns.

3.9 Methodological Limitations

3.9.1 Design Limitations

1. **Cross-sectional design**: Precludes causal inference; relationships may be correlational rather than causal. Future longitudinal studies needed to establish temporal precedence.

2. **Self-reported measures**: Behavioral Intention is a proxy for actual behavior. While BI strongly predicts behavior in UTAUT studies, some intention-behavior gap is expected.

3. **Single time point**: Attitudes and technology contexts change rapidly; findings reflect November 2024 snapshot.

3.9.2 Sampling Limitations

1. **Convenience sampling**: Non-probability sampling limits generalizability to broader populations. Results may not generalize beyond similar United States professional and student contexts.

2. **Single institution**: While diverse roles represented, institutional culture may influence responses.

3. **Self-selection bias**: Participants interested in AI may be overrepresented.

3.9.3 Measurement Limitations

1. **English language only**: Non-English speakers excluded; cross-cultural validity not established.

2. **Two items per construct**: While meeting minimum identification requirements for SEM, more indicators would improve reliability and content coverage.

3. **Adapted scales**: Items adapted from existing instruments; some original validation evidence may not transfer perfectly.

3.9.4 Analytical Limitations

1. **Normality assumptions**: ML estimation assumes multivariate normality; some departures may affect standard errors (though robust methods used where possible).

2. **Common method variance**: Single-source, single-time data collection may inflate correlations. Harman's single-factor test conducted as diagnostic.

3. **Model complexity**: Eight-factor model with limited items requires careful balance between fit and parsimony.

3.10 Chapter Summary

This chapter has described the research methodology for developing and validating the AI Readiness Scale (AIRS) and testing the extended UTAUT model for AI tool adoption. Key methodological features include:

Research Design:

- Post-positivist philosophy with mixed methods approach

- Cross-sectional survey with qualitative supplementation

- United States professionals and students context

Instrument:

- 28 initial items across 12 constructs

- Final validated instrument: 16 items across 8 factors

- 5-point Likert scale measurement

Sample:

- N = 523 United States adults

- Two population groups: Students (216), Professionals (307)

- 50/50 split for cross-validation (EFA n = 261, CFA n = 262)

Analysis:

- 10-phase systematic pipeline

- EFA for structure exploration, CFA for validation

- Multi-group SEM for hypothesis testing

- Cluster analysis for user typology

- Thematic analysis for qualitative insights

Validity:

- Comprehensive reliability and validity assessment

- Measurement invariance across role groups

- Criterion validity through behavioral correlates

The methodology provides a rigorous foundation for the empirical findings presented in Chapter 4, while acknowledging limitations inherent in cross-sectional survey research.

Chapter 4: Findings

4.1 Introduction

This chapter presents the empirical findings from the AI Readiness Survey (AIRS) study examining factors influencing AI tool adoption in higher education. The chapter is organized to progress systematically from sample description through data preparation, quantitative results, and findings organized by research question. All analyses were conducted using Python (factor_analyzer, semopy, scipy, pandas) with a significance level of $\alpha = .05$ unless otherwise specified.

The presentation separates findings from interpretation, following established methodological practice (Yin, 2018). Theoretical and practical implications are addressed in Chapter 5.

4.2 Description of the Sample

The sample comprises N=523 United States adults with representation from both academic and professional contexts. Table 4.1 presents the demographic composition.

4.2.1 Population Composition

Population	n	%	Subgroups
Students	216	41.3%	Full-time (n=196), Part-time (n=20)
Professionals	307	58.7%	Individual contributors (n=112), Managers (n=71), Executives (n=52), Freelancers (n=32), Other (n=23), Unemployed (n=17)

4.2.2 Sample Split for Validation

For psychometric validation, the sample was randomly split (seed=67) into development (n=261, 50%) and holdout (n=262, 50%) subsamples. This split-sample approach enables ex-

ploratory factor analysis on the development sample and independent confirmatory factor analysis on the holdout sample.

4.2.3 Disability Status

Participants with disabilities comprised 13.0% of the sample (n=68), with 11 participants selecting "Prefer not to answer." This representation enables examination of accessibility considerations in AI adoption.

4.3 Data Screening and Preparation

4.3.1 Data Quality Assessment

Data screening confirmed the suitability of the dataset for factor analytic procedures:

- **Missing Data**: Complete case analysis with no missing values on key UTAUT constructs
- **Outliers**: Mahalanobis distance identified 0 multivariate outliers at $p < .001$
- **Normality**: Mardia's test indicated multivariate non-normality; robust estimation (MLM) was employed

4.3.2 Factorability Assessment

The Kaiser-Meyer-Olkin measure of sampling adequacy (KMO = .937) and Bartlett's test of sphericity ($\chi^2 = 4,668.45$, $p < .001$) confirmed the suitability of the correlation matrix for factor analysis.

4.4 Quantitative Findings

This section presents the psychometric validation results, including exploratory and confirmatory factor analyses, reliability assessment, and measurement invariance testing.

4.4.1 Exploratory Factor Analysis (Development Sample)

Exploratory factor analysis was conducted on the development subsample (n=261) to evaluate the underlying factor structure of the AIRS instrument.

Model Selection Process Multiple factor solutions were examined using principal axis factoring with oblimin rotation. The parallel analysis and scree plot suggested retention of 7-9 factors. Based on theoretical alignment with the extended UTAUT framework, the following models were evaluated:

Model	Factors	Items	CFI (CFA)	TLI	RMSEA	SRMR	Decision
A	7	21	.938	.923	.078	.058	Poor fit
B	8	20	.952	.940	.070	.052	Adequate
C	8	18	.964	.953	.066	.048	Good
D	8	16	.975	.960	.065	.046	**Selected**

Model D was selected as the final measurement model based on optimal balance of parsimony and fit, with all items demonstrating factor loadings $\geq .50$ and no substantive cross-loadings $(< .32)$.

Construct Exclusion Analysis Four proposed constructs were excluded during EFA due to poor inter-item reliability:

Construct	Cronbach's α	Decision	Rationale
Voluntariness (VO)	.406	Dropped	Items measured choice vs. freedom—distinct dimensions
Explainability (EX)	.582	Dropped	Items measured understanding vs. preference—distinct facets

Construct	Cronbach's α	Decision	Rationale
Ethical Risk (ER)	.546	Dropped	Items measured job displacement vs. privacy—distinct risk types
AI Anxiety (AX)	.301	Dropped	Items measured avoidance vs. approach anxiety—distinct motivations

Interpretation: The proposed two-item scales for these AI-specific constructs proved insufficient to capture multi-faceted phenomena. This finding highlights a key contribution: while these constructs are theoretically important for AI adoption, they require more comprehensive operationalization with additional items representing each sub-dimension.

Future Development: All four dropped constructs require item redesign for future validation studies. For AI Anxiety specifically, future scales should distinguish between technology avoidance anxiety and fear-of-missing-out (FOMO) or obsolescence anxiety, as these represent conceptually distinct motivational orientations.

Final Factor Structure The validated measurement model comprises 8 predictor factors (16 items) plus Behavioral Intention as the outcome variable (4 items):

Predictor Factors (8 factors, 16 items):

The final measurement model comprises 7 UTAUT2 constructs plus the AI Trust extension:

Factor	Items	Description	α	CR	AVE
Performance Expectancy (PE)	PE1, PE2	Perceived usefulness	.803	.804	.673
Effort Expectancy (EE)	EE1, EE2	Perceived ease of use	.859	.861	.756
Social Influence (SI)	SI1, SI2	Social normative pressure	.752	.763	.621

Factor	Items	Description	α	CR	AVE
Facilitating Conditions (FC)	FC1, FC2	Organizational support	.743	.750	.601
Hedonic Motivation (HM)	HM1, HM2	Enjoyment and curiosity	.864	.865	.763
Price Value (PV)	PV1, PV2	Cost-benefit assessment	.883	.883	.790
Habit (HB)	HB1, HB2	Automaticity of use	.909	.909	.833
AI Trust (TR)	TR1, TR2	Trust in AI systems	.891	.891	.804

Note: BI (Behavioral Intention) serves as the outcome variable and is modeled separately in the structural model.

4.4.2 Confirmatory Factor Analysis (Holdout Sample)

The 8-factor model was cross-validated on the independent holdout sample (n=262) using confirmatory factor analysis in semopy.

Model Fit Assessment

Index	Value	Threshold	Interpretation
χ^2	159.38	—	—
df	76	—	—
χ^2/df	2.10	< 3.0	Excellent
CFI	.975	≥ .95	Excellent
TLI	.960	≥ .95	Excellent
RMSEA	.065	≤ .08	Good
SRMR	.046	≤ .08	Excellent

The model demonstrated excellent fit across all indices, confirming the factor structure derived from the development sample.

Factor Correlations   Inter-factor correlations ranged from r = .25 (Social Influence × Price Value) to r = .72 (Hedonic Motivation × Performance Expectancy), indicating conceptually meaningful

relationships while maintaining discriminant validity (all $|r| < .85$).

4.4.3 Reliability and Validity

Composite Reliability All predictor factors demonstrated acceptable internal consistency:

Factor	Cronbach's α	Composite Reliability (CR)	AVE
PE	.803	.804	.673
EE	.859	.861	.756
SI	.752	.763	.621
FC	.743	.750	.601
HM	.864	.865	.763
PV	.883	.883	.790
HB	.909	.909	.833
TR	.891	.891	.804

Convergent Validity All standardized factor loadings exceeded .70, and all AVE values exceeded .50, supporting convergent validity (Fornell & Larcker, 1981).

Discriminant Validity Discriminant validity was assessed using the Fornell-Larcker criterion. For each factor pair, the square root of AVE exceeded the inter-factor correlation, confirming discriminant validity.

4.4.4 Measurement Invariance (Multi-Group CFA)

Measurement invariance was tested across role groups (Academic n=216 vs. Professional n=307) to establish comparability of latent constructs.

Group	χ^2	df	CFI	TLI	RMSEA	Interpretation
Academic	167.16	76	.958	.934	.075	Good fit
Professional	135.88	76	.988	.981	.051	Excellent fit

Configural invariance was supported: the same factor structure held across both groups.

Metric invariance was not fully achieved (mean loading difference = .082, max = .326), indicating

some factor loadings differ across groups. However, configural invariance is sufficient for comparing structural relationships across groups. The maximum factor loading difference ($\Delta\lambda$ = .326) occurred for the SI factor, though this did not compromise overall model validity.

4.5 Findings by Research Question

This section presents hypothesis testing results organized by research question. The structural model was estimated using multi-group SEM to test hypothesized relationships between UTAUT constructs and Behavioral Intention to adopt AI tools. The model was estimated separately for Student (n=216) and Professional+Leader (n=307) groups.

4.5.1 Structural Model Fit

The structural model demonstrated acceptable fit:

Index	Student	Professional+Leader	Threshold
CFI	.968	.972	$\geq .95$
TLI	.954	.958	$\geq .95$
RMSEA	.072	.068	$\leq .08$
SRMR	.054	.051	$\leq .08$

4.5.2 Primary Hypotheses (H1a–H1g)

Table 4.2 presents the standardized path coefficients and hypothesis test results for the full sample and by role group.

Hypothesis	Path	β	p	Result
H1a	PE $\rightarrow$ BI	-.028	.791	□ Not Supported
H1b	EE $\rightarrow$ BI	-.008	.875	□ Not Supported
H1c	SI $\rightarrow$ BI	**.136**	.024	□ Supported
H1d	FC $\rightarrow$ BI	.059	.338	□ Not Supported
H1e	HM $\rightarrow$ BI	**.217**	.014	□ Supported
H1f	PV $\rightarrow$ BI	**.505**	<.001	□ Supported (Strongest)
H1g	HB $\rightarrow$ BI	.023	.631	□ Not Supported

Hypothesis	Path	β	p	Result
H2	TR → BI	.106	.064	☐ Marginal

Key Findings:

- **Price Value** emerged as the strongest predictor (β = .505, p < .001), explaining the largest portion of variance in Behavioral Intention

- **Hedonic Motivation** was the second strongest predictor (β = .217, p = .014)

- **Social Influence** was a significant positive predictor (β = .136, p = .024)

- **AI Trust** approached but did not reach significance (β = .106, p = .064)

- **Performance Expectancy**, **Effort Expectancy**, **Facilitating Conditions**, and **Habit** were not significant predictors

- Traditional UTAUT predictors showed unexpectedly weak effects, suggesting AI may represent a distinct technology category

4.5.3 Moderation Hypotheses

Usage frequency was tested as a moderator of UTAUT relationships through multi-group SEM comparison.

Usage Group Path Comparison

Predictor	β (Low Usage)	β (High Usage)	Interpretation
PerfExp	0.371*	-0.270	PE matters for new users only
PriceValue	0.224	**0.878***	PV stronger for heavy users

Exploratory Experience Moderation (Regression Interactions)

Moderator	Path	Interaction β	p	Status
Experience	PE×Exp	0.112	.055	☐ Marginal
Experience	**HM×Exp**	**0.136**	**.007**	☐ **Significant**

Moderator	Path	Interaction β	p	Status
Experience	EE×Exp	0.122	.161	☐ Not significant
Experience	TR×Exp	0.081	.145	☐ Not significant

Interpretation:

- **Experience moderates HM → BI** (β = .136, p = .007): Experienced professionals (4+ years) weight hedonic motivation more heavily

- Usage-dependent mechanisms: Performance Expectancy matters for new users; Price Value for heavy users

- Habit is marginally moderated by usage frequency (p = .065)

4.5.4 Population Moderation

Multi-group comparison tested whether structural path coefficients differed significantly between Student and Professional populations.

Path	Student β	Professional β	Δβ	Moderation
PE → BI	-0.184	0.084	0.268	No
EE → BI	0.073	-0.055	-0.128	No
SI → BI	0.007	0.239	0.232	No
FC → BI	-0.016	0.141	0.156	No
HM → BI	0.449	-0.301	-0.750	☐ (p = .041)
PV → BI	0.638	0.808	0.170	No
HB → BI	0.075	-0.064	-0.140	No
TR → BI	-0.011	0.153	0.164	No

Population moderation was partially supported. **Hedonic Motivation** showed a significant population difference (Δβ = -0.750, p = .041), with HM → BI stronger for Students (β = 0.449) than for Professionals (β = -0.301). This suggests enjoyment of AI tools is more important for student adoption than professional adoption. All other paths showed no significant population differences.

4.5.5 Incremental Validity: AIRS vs. UTAUT2-Only Model

To assess whether the AI-specific extension (AI Trust) provides incremental predictive validity beyond core UTAUT2 constructs, nested model comparison was conducted:

Model	Constructs	AIC	BIC	Result
UTAUT2-Only	PE, EE, SI, FC, HM, PV, HB	148.58	192.34	Preferred
AIRS (Extended)	PE, EE, SI, FC, HM, PV, HB, TR	150.59	201.87	—

Result: Although AI Trust showed a marginal effect ($\beta = .106$, $p = .064$), the AIRS model has *higher* AIC (150.59) than UTAUT2-only (148.58), meaning the simpler model is preferred ($\Delta AIC = +2.01$). Lower AIC indicates better parsimony.

Interpretation: This incremental validity test evaluates **predictive parsimony** only—AI Trust may still have **diagnostic value** for identifying trust-related barriers to AI adoption, even if it doesn't improve overall model fit. The marginal significance of AI Trust ($p = .064$) suggests it may achieve significance with larger samples or in contexts where trust concerns are more salient.

4.5.6 Variance Explained

The structural model explained substantial variance in Behavioral Intention:

Group	R^2	Interpretation
Student	.861	86.1% variance explained
Professional+Leader	.852	85.2% variance explained
Full Sample	**.857**	**85.7% variance explained**

This exceptionally high R^2 indicates the UTAUT model, as adapted for AI adoption, captures the vast majority of systematic variance in intention to use AI tools.

4.5.7 Supplementary Analyses

Mediation Hypotheses   Design Note: The originally hypothesized mediation paths (EX → TR → BI, ER → TR → BI) were **not testable** because Explainability (EX), Ethical Risk (ER), and Anxiety (AX) were excluded from the final model due to inadequate item reliability identified in Phase 1 ($\alpha = .301–.582$).

Exploratory Mediation Analysis: Bootstrap mediation testing explored whether AI Trust mediates the effect of Effort Expectancy on Behavioral Intention:

Mediation Path	Indirect Effect	95% CI	p	Result
EE → TR → BI	0.232	[-.023, .474]	> .05	☐ Not Significant

The confidence interval includes zero, indicating no significant mediation. While the theoretical pathway remains conceptually relevant, adding AI Trust as a mediator does not significantly improve the model.

AI Tool Usage Patterns (H5, H6)   Analysis of actual tool usage behaviors provides behavioral validation of intention constructs.

Tool Usage Frequency

AI Tool	Mean Usage	Never Used (%)	Active Use (%)	Leader Effect (d)
ChatGPT	3.03	23.9	64.2	0.74
Microsoft Copilot	2.49	36.1	48.4	1.14
Google Bard/Gemini	2.48	36.5	47.6	0.90
Other AI Tools	1.93	53.3	30.0	0.78

Note: Active Use = "Sometimes" or more frequent usage (≥3 on 5-point scale). Leader Effect = Cohen's d comparing Leaders (Managers/Executives) vs Professionals.

Leadership Dominance: Leaders demonstrated significantly higher usage across ALL tool categories (d = 0.74–1.14), with the largest effect for Microsoft Copilot.

Tool Usage and Behavioral Intention (H5)   The relationship between tool usage frequency and Behavioral Intention was examined using Spearman correlation due to ordinal tool usage distributions.

Relationship	ρ	p	Interpretation
Total Usage × BI	.69	<.001	Strong positive
ChatGPT Usage × BI	.57	<.001	Strong positive
MS Copilot Usage × BI	.54	<.001	Moderate positive
Gemini Usage × BI	.52	<.001	Moderate positive

H5 Result: ☐ Supported – Higher behavioral intention is strongly associated with more frequent AI tool usage.

Role Differences in Tool Usage (H6)   One-way ANOVA with Tukey post-hoc tests examined role differences in tool usage patterns.

Measure	$F_{(2,520)}$	p	η^2	Post-hoc (Tukey)
Tool Breadth	18.42	<.001	.066	L > P > A
Usage Frequency	22.15	<.001	.078	L > P > A
Usage Intensity	15.87	<.001	.058	L > P > A

H6 Result: ☐ Supported – Leaders demonstrate significantly higher tool usage than Professionals, who in turn exceed Academics.

Industry Experience Effect   Among professionals (n=184), correlation between years of industry experience and UTAUT constructs was examined.

Construct	r	p
Performance Expectancy	.10	.176
Behavioral Intention	.08	.284
Anxiety	-.12	.104

Industry experience showed weak, non-significant relationships with UTAUT constructs, suggesting organizational role rather than industry tenure drives AI readiness differences.

4.5.8 Exploratory Findings

User Typology (Cluster Analysis)   K-means cluster analysis (k=4) identified distinct user profiles based on UTAUT construct scores.

Cluster	n	%	PE	HM	AX	BI	Characterization
Enthusiasts	84	16%	High	High	Low	High	Early adopters, high engagement
Cautious Adopters	157	30%	Mod	Mod	Mod	Mod	Pragmatic, wait-and-see
Moderate Users	191	37%	Mod	Low	Mod	Low-Mod	Limited engagement, neutral
Anxious Avoiders	91	17%	Low	Low	High	Low	Resistant, anxiety-driven

Disability Status Analysis   Participants with disabilities (n=68, 13.0%) were compared to those without (n=444):

Construct	Disability M	No Disability M	t	p	d
AX	3.68	3.35	2.77	.006	0.36
EE	3.45	3.67	-1.75	.080	0.23
BI	3.01	3.23	-1.54	.124	0.20

Note: 11 participants selected "Prefer not to answer" and were excluded from this analysis.

Key Finding: Individuals with disabilities reported significantly higher AI-related anxiety (d = 0.36, p = .006), highlighting the importance of accessible and inclusive AI implementation

strategies.

Qualitative Findings   Open-ended responses (n=243, 46.5% response rate) were analyzed using thematic analysis.

Theme Prevalence

Theme	n	% of Responses
Positive Experience	60	24.7%
Work/Productivity	47	19.3%
Human Element	33	13.6%
Learning/Education	33	13.6%
Accuracy/Reliability	26	10.7%
Future/Potential	14	5.8%
Concerns/Caution	14	5.8%
Ethics/Privacy	13	5.3%
Cost/Access	6	2.5%
Job Replacement	4	1.6%

Note: Responses could be coded to multiple themes (average 1.03 themes per response). 85 responses (35.0%) had no identified themes.

Role Differences in Qualitative Themes   Chi-square tests (3-group: Student n=94, Professional n=83, Leader n=66) identified three themes with significant role differences:

Theme	Student %	Professional %	Leader %	χ^2	p	V
Positive Experience	29.8%	14.5%	30.3%	7.11	.029	.17
Learning/Education	21.3%	10.8%	6.1%	8.45	.015	.19
Work/Productivity	28.7%	13.3%	13.6%	8.65	.013	.19

Academics and Leaders reported more positive experiences, while Academics focused more on educational applications.

4.6 Summary of Findings

4.6.1 Hypothesis Summary

Hypothesis	Description	Result
H1a	PE → BI (+)	☐ Not Supported (β = -.028)
H1b	EE → BI (+)	☐ Not Supported (β = -.008)
H1c	SI → BI (+)	☐ Supported (β = .136)
H1d	FC → BI (+)	☐ Not Supported (β = .059)
H1e	HM → BI (+)	☐ Supported (β = .217)
H1f	PV → BI (+)	☐ Supported (β = .505)
H1g	HB → BI (+)	☐ Not Supported (β = .023)
H2	TR → BI (+)	☐ Marginal (p = .064)
H3	Experience moderates paths	☐ Partial (HM×Exp significant, p = .007)
H4	Role group moderates paths	☐ Partial (HM only, p = .041)
H5	BI → Tool Usage	☐ Supported (ρ = .69)
H6	Role usage differences	☐ Supported (F = 22.15, p < .001)

4.6.2 Key Contributions

1. **Price Value Dominance:** PV is the overwhelming driver of AI adoption intention (β = .505), substantially exceeding other predictors and departing from traditional UTAUT findings where PE typically dominates

2. **Experience Moderation Pattern:** AI experience amplifies the effect of HM (p = .007), suggesting experiential learning reinforces enjoyment perceptions

3. **Population Moderation:** Hedonic Motivation is significantly stronger for Academics (β =

0.449) than Professionals (β = -0.301), indicating role-specific adoption drivers

4. **Non-Significance of Traditional UTAUT Predictors:** PE, EE, FC, and HB were not significant, suggesting AI may represent a distinct technology category where cost-value considerations outweigh traditional utility perceptions

5. **User Typology:** Four distinct adoption profiles (Enthusiasts, Cautious Adopters, Moderate Users, Anxious Avoiders) with predictable demographic and attitudinal correlates

4.6.3 Unexpected Findings

- **Non-significant Performance Expectancy:** Contrary to UTAUT predictions and meta-analytic findings, perceived usefulness did not significantly predict adoption intention (β = -.028, p = .791), possibly because utility is a baseline expectation for AI tools
- **Non-significant Effort Expectancy:** Perceived ease of use did not significantly predict adoption intention, possibly due to the user-friendly nature of modern AI interfaces
- **Price Value as Strongest Predictor:** The dominance of cost-value perceptions over utility perceptions represents a notable departure from prior UTAUT research

4.7 Chapter Conclusion

This chapter presented comprehensive empirical validation of the AIRS instrument and structural model examining AI adoption in higher education. The 8-factor, 16-item measurement model demonstrated excellent psychometric properties (CFI = .975, α range .74–.91) with configural invariance across role groups.

Structural equation modeling revealed Price Value as the dominant predictor of Behavioral Intention (β = .505), followed by Hedonic Motivation (β = .217, p = .014) and Social Influence (β = .136, p = .024). AI Trust approached but did not reach significance (β = .106, p = .064). Notably, traditional UTAUT predictors including Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Habit were not significant, suggesting AI tools may represent a distinct technology

category. Experience moderated the HM pathway, while population moderated HM effects with academics weighting enjoyment more heavily than professionals.

Exploratory analyses identified four user typologies and qualitative themes reflecting both enthusiasm and concern about AI integration in higher education. These findings provide a robust foundation for the theoretical and practical implications discussed in Chapter 5.

Chapter 5: Analysis and Discussion

5.1 Introduction

This chapter interprets the empirical findings presented in Chapter 4, connecting the results to the theoretical framework and existing literature. The analysis proceeds systematically through each major finding, examining its meaning, comparing it with prior research, and exploring implications for both theory and practice. Unexpected findings and study limitations specific to interpretation are also addressed. Comprehensive conclusions, recommendations, and future research directions are presented in Chapter 6.

5.2 Interpretation of Findings

5.2.1 AIRS Instrument Validation

The study successfully validated an 8-factor, 16-item AI Readiness Scale extending UTAUT2 with AI Trust. The instrument demonstrated excellent psychometric properties across both development (n = 261) and holdout (n = 262) samples, with fit indices exceeding conventional thresholds (CFI = .975, TLI = .960, RMSEA = .065, SRMR = .048).

The cross-validation design—rarely employed in scale development research—provides strong evidence for the generalizability of the factor structure. The successful demonstration of configural invariance across student and professional populations further supports the instrument's utility for diverse workplace contexts, though metric invariance was not fully achieved (mean $\Delta\lambda$ = .082, max $\Delta\lambda$ = .326).

5.2.2 Structural Model Results

Three of seven hypothesized UTAUT2 paths were significant:

- **Price Value** (β = .505, p < .001): Cost-benefit perception is the dominant driver
- **Hedonic Motivation** (β = .217, p = .014): Enjoyment significantly predicts adoption

- **Social Influence** (β = .136, p = .024): Peer influence matters for AI adoption

The AI Trust extension approached but did not reach significance (β = .106, p = .064), providing tentative support for the theoretical extension. Notably, traditional UTAUT predictors including Performance Expectancy, Effort Expectancy, Facilitating Conditions, and Habit were not significant predictors.

5.3 Comparison with Existing Literature

5.3.1 Price Value as Dominant Predictor

Finding: Price Value emerged as the overwhelmingly strongest predictor (β = .505, p < .001), substantially exceeding all other constructs.

Comparison with Prior Research: This finding represents a significant departure from traditional UTAUT research where Performance Expectancy typically dominates. Blut et al.'s (2022) meta-analysis of 737,112 users found Performance Expectancy to be the strongest predictor (ρ = .60) across technology contexts. The reversal observed in this study suggests fundamental differences in how users evaluate AI tools compared to conventional technologies.

Industry Context: This Price Value dominance gains practical significance when contextualized against the enterprise AI adoption landscape. Despite 88% of organizations now using AI in at least one business function (McKinsey & Company, 2025), only 6% qualify as "AI high performers"—those achieving measurable returns across multiple use cases (McKinsey & Company, 2025). The Boston Consulting Group reports that 74% of companies struggle to scale AI beyond pilot projects and only 5% achieve measurable ROI (Boston Consulting Group, 2024). This "adoption-value gap" suggests that organizations are deploying AI without effectively communicating or demonstrating value to end users—precisely the construct captured by Price Value.

Interpretation: In the AI context, users appear primarily motivated by **perceived value relative to cost** rather than raw productivity benefits (PE, ns), ease of use (EE, ns), organizational support (FC, ns), or habit (HB, ns). This suggests that AI adoption interventions should priori-

tize demonstrating clear return on investment and cost-effectiveness rather than focusing solely on capability demonstrations.

Theoretical Implications: The dominance of Price Value over Performance Expectancy suggests AI tools may represent a distinct technology category. Unlike previous technologies where utility perceptions drove adoption, AI adoption appears more influenced by value propositions—potentially reflecting the freemium pricing models common in AI tools, concerns about ongoing subscription costs, or cost-benefit analyses comparing AI tools to traditional methods.

5.3.2 Non-Significant UTAUT2 Paths

Finding: PE, EE, FC, and HB were not significant predictors.

Comparison with Prior Research: The non-significance of Performance Expectancy (β = -.028, p = .791) is particularly noteworthy given its historical dominance in technology acceptance research. Davis's (1989) TAM established perceived usefulness as the primary adoption driver, and this finding has been replicated across thousands of studies. The present results challenge this assumption for AI contexts.

Industry Context: The non-significance of Effort Expectancy and Facilitating Conditions aligns with industry observations about modern AI implementation. According to Deloitte, 60% of organizations report insufficient AI expertise as a primary barrier (Deloitte, 2024)—yet users in this study did not cite ease-of-use or organizational support as adoption drivers. This disconnect suggests a maturation in AI tool interfaces: contemporary consumer-facing AI (e.g., ChatGPT, GitHub Copilot) has achieved such usability that effort perceptions no longer differentiate adoption decisions. The barrier has shifted from "Can I use this?" to "Is it worth my investment?"

Interpretation: In the AI context, perceived usefulness may be a baseline expectation rather than a differentiating factor. Users may assume AI tools will enhance productivity, making cost-benefit considerations (Price Value) and enjoyment (Hedonic Motivation) the deciding factors.

Similarly, the non-significance of Effort Expectancy (β = -.008, p = .875) and Facilitating

Conditions (β = .059, p = .338) may reflect the increasingly user-friendly nature of modern AI tools and widespread organizational technology infrastructure. Contemporary AI interfaces have achieved remarkable usability, potentially creating ceiling effects for ease-of-use perceptions.

5.3.3 AI Trust Marginality

Finding: TR approached but did not reach significance (β = .106, p = .064).

Comparison with Prior Research: Emerging AI adoption research has increasingly emphasized trust as a critical determinant (Glikson & Woolley, 2020; Siau & Wang, 2018). The marginal effect observed here partially supports this theoretical direction while highlighting the need for more sensitive measurement or larger samples.

Industry Context: The marginal significance of AI Trust resonates with industry findings on governance and accountability barriers. Gartner reports that more than 40% of AI projects experience delays due to governance, compliance, or accountability issues (Gartner, 2025). The Georgian AI Benchmark found that only 32% of organizations have achieved cross-functional AI deployment, with trust and governance cited as key inhibitors (Georgian & NewtonX, 2025). These industry challenges suggest that trust—while marginally significant at the individual level—may become increasingly central as AI applications mature and governance requirements intensify.

Interpretation: The marginal significance of AI Trust suggests it may become a more important predictor as AI technologies mature and trust concerns become more salient. The current sample may have insufficient power to detect the effect (β = .106 requires n > 600 for 80% power at α = .05), or trust considerations may be less central for the relatively straightforward AI tools currently in use. Future research should examine whether AI Trust becomes more predictive for high-stakes AI applications (e.g., AI-assisted decision-making, autonomous systems).

5.3.4 Experience as Moderator

Finding: Professional experience strengthens HM $\rightarrow$ BI (β = .136, p = .007).

Comparison with Prior Research: While UTAUT specifies experience as a moderator, it

conceptualizes experience as technology familiarity rather than career development. The present finding integrates career development theory (Super, 1980) with technology acceptance, suggesting that vocational maturity influences technology evaluation processes.

Interpretation: The significant moderation effect suggests that experienced professionals place greater weight on enjoyment when evaluating AI tools. This may reflect that experienced users, having satisfied basic competency needs, prioritize intrinsic satisfaction. Additionally, usage frequency moderates the importance of Performance Expectancy (for new users) versus Price Value (for heavy users).

5.4 Implications for Theory

5.4.1 UTAUT2 Extension

The study extends UTAUT2 with AI-specific constructs, demonstrating that traditional technology acceptance frameworks require context-sensitive modification. The dramatic shift in predictor importance—from Performance Expectancy dominance to Price Value dominance—suggests that AI represents a theoretically distinct technology category.

5.4.2 Context-Specific Model

The findings support calls for domain-specific UTAUT extensions (Blut et al., 2022). Rather than applying generic technology acceptance models, researchers should develop and validate context-appropriate extensions that capture the unique psychological processes relevant to each technology category.

5.4.3 Career Development Integration

The significant experience moderation effect introduces career development as a relevant theoretical domain for technology acceptance research. Future models should consider how career stage and professional identity influence technology evaluation and adoption decisions.

5.4.4 User Typology Framework

The empirically-derived four-segment typology provides a practical framework for understanding adoption heterogeneity:

- **AI Enthusiasts (16%)**: High adoption readiness, positive affect toward AI
- **Cautious Adopters (30%)**: Moderate interest with reservations requiring address
- **Moderate Users (37%)**: Pragmatic orientation focused on specific benefits
- **Anxious Avoiders (17%)**: Elevated anxiety requiring targeted intervention

This segmentation approach moves beyond mean-level analysis to acknowledge individual differences in adoption psychology.

5.5 Implications for Practice

The findings from this study offer insights for organizations navigating AI adoption challenges. With 88% of enterprises now deploying AI but only 6% achieving "high performer" status with measurable returns (McKinsey & Company, 2025), the gap between adoption and value realization represents a critical business challenge. While this study validates a measurement instrument rather than testing interventions, the empirical findings suggest several evidence-informed directions for practitioners.

Important Scope Note: The AIRS instrument validated in this study provides a psychometrically sound measure of AI adoption readiness constructs. The practical applications suggested below are hypotheses derived from the empirical findings—future experimental research is needed to validate intervention effectiveness. The author's research roadmap includes developing formal AIRS Score algorithms, diagnostic protocols, and intervention frameworks as subsequent research phases.

5.5.1 For Organizations

Lead with Value, Not Capabilities: The dominance of Price Value ($\beta = .505$) over Performance Expectancy (ns) suggests a potential shift in how organizations might approach AI implementation communications. Rather than emphasizing AI capabilities and productivity promises, the findings suggest that demonstrating return on investment and cost-effectiveness may be more influential. Capgemini's research supports this direction, finding that organizations redesigning workflows around AI—rather than simply adding AI to existing processes—achieve 1.7 times higher ROI (Capgemini Research Institute, 2025).

Consider Adoption Heterogeneity: The four-segment typology suggests that user populations vary systematically in their AI readiness profiles:

- **AI Enthusiasts (16%)**: May serve as early adopters and potential peer champions
- **Cautious Adopters (30%)**: May respond to evidence-based value demonstrations
- **Moderate Users (37%)**: May focus on specific, high-value use cases
- **Anxious Avoiders (17%)**: May require attention to emotional barriers before technical training

Leadership Engagement: Leaders in this study demonstrated the highest AI tool usage ($d = 0.74$–1.14). McKinsey's research confirms that organizations where senior leadership takes ownership of AI initiatives are three times more likely to achieve value from their investments (McKinsey & Company, 2025). Visible leadership engagement may amplify adoption efforts.

5.5.2 For AI Tool Designers

Pricing strategy may significantly influence adoption—potentially more so than feature development. The dominance of Price Value suggests that pricing models (freemium tiers, transparent costs, usage-based billing) warrant careful attention. The significant Hedonic Motivation effect ($\beta = .217$) also suggests value in investing in enjoyable user experiences.

5.5.3 For Trainers and Educators

The identification of an "Anxious Avoider" segment (17%) suggests that training programs may benefit from addressing emotional barriers alongside technical skills. The disability-anxiety association (d = .36) highlights the importance of accessibility-centered training design. These findings warrant experimental validation of anxiety-reduction approaches in AI training contexts.

5.5.4 For Policy Makers

The validated AIRS instrument provides a foundation for future organizational AI readiness assessment research. The differential anxiety findings (disability association d = .36) highlight equity considerations in AI adoption policy that warrant further investigation.

5.5.5 Understanding the Adoption-Value Gap

This study's findings offer insights into mechanisms that may contribute to the widely-documented gap between AI adoption rates and value realization. MIT Media Lab's estimate that 90–95% of generative AI pilots fail to scale (MIT Media Lab, 2025) reflects challenges that this research begins to illuminate:

1. **Value Communication Misalignment**: Organizations may lead with capability demonstrations (Performance Expectancy) when users actually evaluate cost-benefit ratios (Price Value). Future research should test whether value-focused messaging improves adoption outcomes.

2. **Heterogeneous Adoption Readiness**: One-size-fits-all implementation approaches may fail because user populations vary systematically. The four-segment typology provides a framework for future intervention research.

3. **Neglected Affective Barriers**: The 17% Anxious Avoider segment and marginal Trust effect suggest that psychological barriers may be underaddressed in current practice.

4. **Context-Inappropriate Frameworks**: Applying generic technology acceptance models to AI contexts may lead to misallocated resources. The dramatic shift from Performance Expectancy dominance to Price Value dominance demonstrates why context-specific measurement instruments are valuable.

5.6 Unexpected Findings

5.6.1 Performance Expectancy Non-Significance

The non-significance of Performance Expectancy was unexpected given its historical dominance in technology acceptance research. This finding suggests that AI adoption operates through different psychological mechanisms than conventional technology adoption, potentially because productivity benefits are now assumed rather than evaluated.

5.6.2 Dropped Constructs

Four proposed AI-specific constructs demonstrated inadequate reliability and were excluded:

Construct	Cronbach's α	Issue Identified
Voluntariness	.406	Choice vs. freedom dimensions conflated
Explainability	.582	Understanding vs. preference dimensions conflated
Ethical Risk	.546	Job displacement vs. privacy dimensions conflated
AI Anxiety	.301	Avoidance vs. approach motivations conflated

Interpretation: Two-item scales proved insufficient for these multi-dimensional constructs. This represents an empirical finding about measurement complexity rather than theoretical invalidity. These constructs remain important for AI adoption theory but require more comprehensive operationalization with 3-4 items per sub-dimension.

5.6.3 Disability and Accessibility

Finding: Disability associated with higher AI-related anxiety responses (d = .36), based on exploratory analysis of original AX items prior to exclusion.

Interpretation: This unexpected finding highlights accessibility considerations in AI adoption. Users with disabilities may experience heightened anxiety about AI technologies, potentially due to concerns about accessibility, job displacement, or past negative experiences with technology. Inclusive AI design and training approaches are warranted.

5.7 Study Limitations Affecting Interpretation

Several limitations should be considered when interpreting these findings:

5.7.1 Methodological Limitations

1. **Cross-sectional design**: The single time-point data collection precludes causal inference. While SEM estimates suggest directional relationships, alternative causal orderings (e.g., behavior → intention) cannot be ruled out.

2. **Self-reported intention**: Behavioral Intention may not perfectly predict actual behavior. However, the strong BI-Usage correlation ($\rho = .69$) provides behavioral validation.

3. **Convenience sampling**: The United States sample limits generalizability to other countries, cultures, and organizational contexts.

5.7.2 Measurement Limitations

1. **Dropped constructs**: The exclusion of four proposed constructs limits the comprehensiveness of the theoretical extension. The originally proposed mediation hypotheses involving Explainability and Ethical Risk could not be tested because these constructs were excluded during EFA due to inadequate reliability.

2. **Marginal AI Trust**: Trust approached but did not reach significance (p = .064). This may reflect inadequate statistical power (β = .106 requires n > 600 for 80% power at α = .05) or genuine marginality of trust in current AI adoption decisions.

3. **Western sample**: Cultural generalizability is unknown. AI adoption attitudes may differ substantially in collectivist cultures or regions with different AI policy environments.

Chapter 6: Conclusions, Implications, and Recommendations

6.1 Introduction

This concluding chapter synthesizes the contributions of this dissertation study and articulates its significance for both scholarly advancement and organizational practice. The chapter summarizes the research purpose, methodology, and key findings; discusses theoretical and practical contributions; provides recommendations for practitioners and organizations; acknowledges limitations; suggests directions for future research; and offers closing remarks on the broader implications of this work for AI adoption in professional contexts.

6.2 Summary of Purpose, Methods, and Key Findings

6.2.1 Research Purpose

This study addressed a critical gap in technology acceptance research: the inadequacy of existing frameworks to explain AI-specific adoption patterns. While traditional models like UTAUT2 have demonstrated robust explanatory power for conventional technologies, the unique characteristics of AI systems—including opacity, probabilistic reasoning, and ethical implications—necessitate theoretical extension. The research purpose was twofold: (1) to develop and validate a psychometrically sound AI Readiness Scale (AIRS) extending UTAUT2 with AI-specific constructs, and (2) to identify the key drivers of AI adoption intention in professional and academic contexts.

6.2.2 Methodology Summary

The study employed a rigorous ten-phase psychometric validation approach:

0. **Sample Splitting**: Created stratified EFA/CFA subsamples (n = 261/262) with random seed = 67 for reproducibility

1. **Exploratory Factor Analysis** (n = 261): Identified the underlying factor structure through

split-sample design

2. **Confirmatory Factor Analysis** (n = 262): Cross-validated the measurement model on an independent holdout sample

3. **Measurement Invariance Testing**: Established configural invariance across student and professional populations (metric invariance not fully achieved)

4. **Structural Equation Modeling**: Tested hypothesized relationships among latent constructs

5. **Mediation Analysis**: Examined indirect effects within the structural model

6. **Moderation Analysis**: Investigated experience and usage frequency as boundary conditions

7. **Behavioral Validation**: Correlated intentions with actual AI tool usage patterns

8. **Qualitative Analysis**: Thematic analysis of open-ended responses

9. **Comprehensive Review**: Gap analysis and cross-validation of findings

10. **Final Synthesis**: Integration of quantitative and qualitative insights

This multi-phase approach exceeds typical scale development standards and provides robust evidence for the AIRS instrument's validity.

6.2.3 Key Findings

The study produced several significant findings that advance both theory and practice:

Instrument Validation: The 8-factor, 16-item AIRS demonstrated excellent psychometric properties (CFI = .975, RMSEA = .065, α range .743–.909, all CR > .750, all AVE > .601) and configural invariance across populations, establishing a validated foundation for future AI readiness assessment applications.

Adoption Drivers: Contrary to expectations from traditional UTAUT research, Price Value emerged as the dominant predictor (β = .505, p < .001), followed by Hedonic Motivation (β = .217, p = .014) and Social Influence (β = .136, p = .024). Traditional predictors including Performance Expectancy, Effort Expectancy, and Facilitating Conditions were not significant.

AI Trust Extension: AI Trust approached but did not reach conventional significance (β = .106, p = .064), providing tentative support for the theoretical extension while highlighting the

need for larger samples in future research.

Moderator Effects: Professional experience strengthened the Hedonic Motivation → Behavioral Intention path (β = .136, p = .007), suggesting that experienced professionals prioritize enjoyment in AI tool evaluation.

User Typology: Four distinct adoption segments were identified—AI Enthusiasts (16%), Cautious Adopters (30%), Moderate Users (37%), and Anxious Avoiders (17%)—suggesting heterogeneous adoption readiness patterns that future research can leverage for intervention design.

6.3 Theoretical Contributions

This dissertation makes four primary contributions to technology acceptance theory:

6.3.1 UTAUT2 Extension for AI Contexts

The study extends UTAUT2 with AI-specific constructs, demonstrating that traditional technology acceptance frameworks require modification for AI adoption contexts. While AI Trust did not reach conventional significance, the near-significant effect (p = .064) and the dramatic shift in predictor importance (Price Value dominance over Performance Expectancy) suggest that AI represents a theoretically distinct technology category requiring dedicated research attention.

6.3.2 Context-Specific Adoption Drivers

The finding that Price Value, rather than Performance Expectancy, drives AI adoption represents a significant departure from decades of technology acceptance research. This suggests that users evaluate AI tools through a value lens rather than a utility lens—they ask "Is it worth it?" rather than "Will it help me?" This reframing has important implications for how AI adoption should be theorized and measured.

6.3.3 Career Development Integration

The significant moderation effect of professional experience on the Hedonic Motivation → Behavioral Intention path introduces career development as a relevant theoretical domain for technology acceptance research. As professionals advance in their careers, intrinsic satisfaction becomes more important relative to instrumental benefits, suggesting that adoption models should incorporate career-stage considerations.

6.3.4 User Typology Framework

The empirically-derived four-segment typology provides insights into adoption heterogeneity that can inform future intervention research. Rather than treating users as a homogeneous population, this segmentation reveals that different psychological profiles may respond to different adoption strategies—a hypothesis warranting future experimental validation.

6.4 Practical and Managerial Implications

6.4.1 For Organizations Implementing AI

Value Demonstration Over Capability Showcasing: The dominance of Price Value suggests that organizations should focus on demonstrating clear return on investment rather than simply highlighting AI capabilities. Implementation programs should quantify productivity gains, cost savings, and competitive advantages in terms that resonate with employees' cost-benefit mental models.

Segment-Specific Intervention Design: The four-segment user typology provides a framework for tailored change management: - **AI Enthusiasts (16%)**: Deploy as champions and early adopters who can influence peers - **Cautious Adopters (30%)**: Provide evidence-based reassurance and hands-on training - **Moderate Users (37%)**: Focus messaging on specific, relevant benefits - **Anxious Avoiders (17%)**: Implement targeted anxiety-reduction interventions before capability training

Social Influence Leverage: The significant Social Influence effect ($\beta = .136$) suggests that peer influence matters for AI adoption. Organizations should cultivate visible AI champions and create communities of practice where positive experiences are shared.

Experience-Sensitive Approaches: The moderation finding suggests that experienced professionals should receive different messaging than newer employees. For senior staff, emphasize the intrinsic satisfaction and intellectual engagement that AI tools provide; for junior staff, focus on value propositions and career development benefits.

6.4.2 For AI Tool Designers and Vendors

Pricing Model Innovation: The Price Value dominance suggests that pricing strategy significantly influences adoption. Freemium models, transparent pricing, and clear ROI documentation may be more important than feature development for driving adoption.

Trust-Building Features: While AI Trust was marginally significant, its near-significance ($p = .064$) suggests that trust considerations are emerging concerns. Designers should invest in explainability features, reliability demonstrations, and transparency mechanisms that address trust-related hesitation.

Enjoyment-Focused Design: The Hedonic Motivation effect indicates that users value enjoyable experiences. AI tools should be designed not just for utility but for engagement, incorporating elements that make interaction satisfying and even fun.

6.4.3 For Trainers and Educators

Anxiety-Informed Pedagogy: The identification of an "Anxious Avoider" segment (17%) with elevated AI anxiety suggests that training programs should address emotional barriers before technical skills. Anxiety-reduction interventions—such as gradual exposure, peer support, and psychological safety—should precede capability training.

Accessibility Considerations: The finding that disability status is associated with higher AI anxiety ($d = .36$) highlights the need for inclusive AI training design. Trainers should ensure that

materials and interfaces accommodate diverse abilities and that anxious learners receive appropriate support.

6.4.4 For Policy Makers and Organizational Leaders

Workforce Readiness Research: The validated AIRS instrument provides a foundation for future organizational AI readiness assessment research. Policy makers may benefit from population-level assessments, though such applications require additional validation beyond the scope of this scale development study.

Equity Considerations: The differential anxiety findings suggest that AI adoption may create or exacerbate workforce inequities. Policies should ensure that all employees—regardless of experience level, disability status, or initial anxiety—have equitable access to AI benefits.

6.5 Recommendations

6.5.1 Recommendations for Scholars

Based on the empirical findings and identified research gaps, the following recommendations are offered for the academic community:

1. **Replicate with larger samples**: The marginal AI Trust effect (β = .106, p = .064) warrants replication with n > 600 to achieve adequate statistical power for detecting small-to-medium effects in AI adoption contexts.

2. **Develop improved AI-specific measures**: The dropped constructs (Voluntariness, Explainability, Ethical Risk) represent important theoretical concepts that require more comprehensive operationalization with 3-4 items per sub-dimension and rigorous cognitive interviewing.

3. **Investigate Price Value dominance**: The unexpected finding that Price Value rather than Performance Expectancy drives AI adoption merits theoretical attention. Scholars should

explore whether this reflects AI's unique characteristics or broader shifts in technology evaluation patterns.

4. **Examine career development integration**: The significant experience moderation effect on Hedonic Motivation suggests that career development theory should be integrated with technology acceptance models. Longitudinal research linking career stages to adoption trajectories is warranted.

5. **Validate the user typology framework**: The four-segment typology (Enthusiasts, Cautious Adopters, Moderate Users, Anxious Avoiders) should be validated across populations and used to develop segment-specific theoretical models.

6. **Conduct cross-cultural research**: The Western sample limits generalizability. Comparative studies in collectivist cultures, developing economies, and regions with different AI policy environments are essential for theory refinement.

7. **Apply longitudinal designs**: Cross-sectional limitations preclude causal inference. Panel studies tracking intention-behavior relationships over 6-12 months will strengthen theoretical claims.

6.5.2 Recommendations for Practitioners

The following recommendations are offered with an important caveat: this study validates a measurement instrument and identifies adoption drivers, but does not experimentally test interventions. The recommendations below represent evidence-informed hypotheses derived from the empirical findings, pending future intervention research:

1. **Consider baseline AIRS assessment** before implementing AI initiatives to understand the distribution of adoption readiness in the population. The validated instrument can inform planning, though formal diagnostic protocols require additional development.

2. **Lead with value propositions** rather than capability demonstrations. The dominance of Price Value ($\beta = .505$) over Performance Expectancy (ns) suggests communicating AI benefits in terms of time savings, cost reduction, and ROI rather than technical features.

3. **Attend to affective barriers**: The 17% "Anxious Avoider" segment and marginal Trust effect suggest that emotional responses to AI warrant attention. Future research should test whether anxiety-reduction approaches (gradual exposure, peer support, psychological safety) improve adoption outcomes.

4. **Leverage social influence** by identifying and supporting AI champions who can model positive adoption behaviors. Social Influence was a significant predictor ($\beta = .136$), suggesting peer effects matter.

5. **Differentiate by experience level**: The significant experience moderation effect suggests that newer employees may weight different factors than senior professionals when evaluating AI tools.

6. **Monitor trust perceptions** as AI applications become more consequential. The marginal Trust effect ($p = .064$) suggests that trust may become more important as AI moves into higher-stakes decision-making roles.

7. **Design for accessibility** to ensure that AI adoption does not disadvantage employees with disabilities or those who experience higher baseline technology anxiety ($d = .36$ disability-anxiety association).

8. **Consider segment heterogeneity**: The four-segment user typology suggests that different groups may respond to different approaches. Experimental research is needed to determine whether segment-specific interventions outperform one-size-fits-all approaches.

6.6 Limitations of the Study

While this study employed rigorous methodology and produced robust findings, several limitations should be acknowledged:

6.6.1 Methodological Limitations

Cross-Sectional Design: The single time-point data collection precludes causal inference. While structural equation modeling suggests directional relationships, alternative causal orderings cannot be ruled out. Longitudinal research is needed to establish temporal precedence.

Self-Reported Intention: Behavioral Intention may not perfectly predict actual behavior. However, the strong correlation between intention and self-reported usage ($\rho = .69$) provides behavioral validation.

Convenience Sampling: The United States sample limits generalizability to other countries, cultures, and organizational contexts. Replication in diverse settings is recommended.

6.6.2 Measurement Limitations

Dropped Constructs: Four proposed AI-specific constructs (Voluntariness, Explainability, Ethical Risk, and AI Anxiety) demonstrated inadequate reliability ($\alpha = .301–.582$) and were excluded from the validated model. This represents an empirical finding about measurement challenges rather than a design failure, but it limits the comprehensiveness of the theoretical extension.

Marginal AI Trust Effect: The Trust effect ($\beta = .106$, $p = .064$) did not reach conventional significance, possibly due to inadequate statistical power. Larger samples may be required to detect this effect reliably.

Western Sample: Cultural generalizability is unknown. AI adoption attitudes may differ substantially in collectivist cultures or regions with different AI policy environments.

6.7 Recommendations for Future Research

6.7.1 Immediate Research Priorities

1. **Larger Sample Replication**: Achieve n > 600 to provide adequate power (80%) for detecting small effects like the Trust coefficient ($\beta \approx .106$).

2. **Dropped Construct Development**: Redesign measures for Voluntariness, Explainability, Ethical Risk, and Anxiety sub-dimensions using 3-4 items per dimension and cognitive interviewing procedures.

3. **Longitudinal Validation**: Track actual AI adoption behavior over 6-12 months following intention measurement to validate the intention-behavior pathway.

4. **Mediation Hypothesis Testing**: With improved measures, test the originally hypothesized mediation paths through Explainability and Ethical Risk.

6.7.2 Extended Research Agenda

1. **Cross-Cultural Validation**: Replicate the AIRS in collectivist cultures, developing economies, and regions with different AI policy environments.

2. **Industry-Specific Adaptation**: Examine whether AI adoption drivers differ across industries (e.g., healthcare, finance, education) where AI applications and risk profiles vary.

3. **Intervention Effectiveness Studies**: Design and evaluate segment-specific interventions based on the user typology framework to determine whether the identified segments respond differently to targeted approaches.

4. **Accessibility Research**: Investigate the mechanisms underlying the disability-anxiety association and develop inclusive AI training approaches.

5. **High-Stakes AI Contexts**: Examine whether Trust becomes more predictive for consequential AI applications such as autonomous decision-making systems.

6.7.3 Research Roadmap: From Validated Scale to Organizational Applications

This dissertation establishes the AIRS as a validated measurement instrument. The following roadmap outlines the research program required to develop practical organizational applications:

Phase 1: AIRS Score Development (Near-term) - Develop a scoring algorithm that transforms raw item responses into interpretable individual and organizational readiness scores - Establish normative benchmarks across populations (students, professionals, leaders) - Create percentile rankings and readiness classifications (e.g., "emerging," "developing," "proficient," "advanced") - Validate score interpretations through criterion-related validity studies linking scores to actual adoption outcomes

Phase 2: Diagnostic Protocol Development (Medium-term) - Design administration protocols for organizational AI readiness assessment - Develop reporting frameworks that translate AIRS results into actionable organizational insights - Pilot diagnostic protocols with partner organizations - Establish reliability of organizational-level aggregated scores

Phase 3: Intervention Framework Development (Medium-term) - Design experimental studies testing segment-specific interventions: - Enthusiasts: Champion program effectiveness - Cautious Adopters: Evidence-based reassurance interventions - Moderate Users: Use-case targeting approaches - Anxious Avoiders: Anxiety-reduction protocols (graduated exposure, psychological safety, peer support) - Conduct randomized controlled trials to establish intervention effectiveness - Develop practitioner guides for evidence-based intervention selection

Phase 4: Comprehensive AI Readiness System (Long-term) - Integrate validated AIRS Score, diagnostic protocols, and intervention frameworks into a comprehensive organizational AI readiness system - Develop longitudinal tracking capabilities for monitoring readiness progression - Create industry-specific adaptation guidelines - Establish training and certification for AIRS practitioners

This roadmap positions the current validated scale as the essential foundation for a research-

to-practice pipeline that can ultimately deliver the diagnostic and intervention tools that organizations need to close the AI adoption-value gap.

6.8 Closing Remarks

This dissertation addresses a timely and consequential challenge: understanding why individuals adopt or resist AI tools in professional contexts. At a time when organizational AI adoption has reached approximately 76% while only 1% of organizations consider themselves "AI mature," the gap between technology availability and effective utilization demands scholarly attention.

The findings reveal that AI adoption is not simply an extension of previous technology acceptance patterns. The dominance of Price Value over Performance Expectancy, the significant role of Hedonic Motivation, and the emergence of experience as a moderator suggest that AI represents a distinct technology category requiring dedicated theoretical and practical attention. Users evaluate AI tools through a value-and-enjoyment lens rather than a pure utility lens—a finding with profound implications for how organizations message, train, and support AI adoption.

The validated AIRS instrument provides researchers with a psychometrically sound foundation for investigating AI adoption patterns. The four-segment user typology offers preliminary evidence of adoption heterogeneity that warrants future experimental investigation. And the theoretical extensions contribute to the ongoing scholarly conversation about how technology acceptance models must evolve to address emerging technologies.

As AI continues to transform professional work, understanding the psychological drivers of adoption becomes increasingly critical. This dissertation offers a validated theoretical foundation and measurement instrument that can enable future diagnostic tools, intervention protocols, and organizational assessment systems. The author's research roadmap includes developing an AIRS Score algorithm for individual and organizational benchmarking, designing and testing segment-specific interventions, and validating the instrument across diverse cultural and industry contexts. The path forward requires continued research, experimental intervention studies, and commitment to inclusive adoption that benefits all members of the workforce.

References

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

Al-Qaysi, N., Mohamad-Nordin, N., & Al-Emran, M. (2020). Employing the technology acceptance model in social media: A systematic review. *Education and Information Technologies*, *25*, 4961–5002. https://doi.org/10.1007/s10639-020-10197-1

Baddeley, A. D., & Hitch, G. (1974). Working memory. *Psychology of Learning and Motivation*, *8*, 47–89. https://doi.org/10.1016/S0079-7421(08)60452-1

Boston Consulting Group. (2024). *AI at scale: Overcoming the barriers to enterprise AI adoption* [Research Report]. Boston Consulting Group. https://www.bcg.com/publications/2024/overcoming-barriers-to-enterprise-ai-adoption

Boston Consulting Group. (2025). *The widening AI value gap: Why only 5 percent of companies realize measurable returns from AI* [Research Report]. Boston Consulting Group. https://www.bcg.com/publications/2025/widening-ai-value-gap

Braun, V., & Clarke, V. (2006). Using thematic analysis in psychology. *Qualitative Research in Psychology*, *3*(2), 77–101. https://doi.org/10.1191/1478088706qp063oa

Bubeck, S., Chandrasekaran, V., Eldan, R., Gehrke, J., Horvitz, E., Kamar, E., Lee, P., Lee, Y. T., Li, Y., Lundberg, S., Nori, H., Palangi, H., Ribeiro, M. T., & Zhang, Y. (2023). Sparks of artificial general intelligence: Early experiments with GPT-4. *arXiv Preprint*. https://doi.org/10.48550/arXiv.2303.12712

Byrne, B. M., Shavelson, R. J., & Muthén, B. (1989). Testing for the equivalence of factor covariance and mean structures: The issue of partial measurement invariance. *Psychological Bulletin*, *105*(3), 456–466. https://doi.org/10.1037/0033-2909.105.3.456

Capgemini Research Institute. (2024). *Harnessing the value of generative AI* (2nd ed.) [Research Report]. Capgemini Research Institute. https://www.capgemini.com/research/harnessing-the-value-of-generative-ai-2nd-edition

Capgemini Research Institute. (2025). *AI in action: How generative AI and agentic AI redefine business operations* [Research Report]. Capgemini Research Institute. https://www.capgemini.com/research/ai-in-action-2025

Chatterjee, S., & Bhattacharjee, K. K. (2021). Adoption of artificial intelligence in higher education: A quantitative analysis using structural equation modelling. *Education and Information Technologies*, *26*(3), 3443–3463. https://doi.org/10.1007/s10639-020-10374-2

Chen, F. F. (2007). Sensitivity of goodness of fit indexes to lack of measurement invariance. *Structural Equation Modeling*, *14*(3), 464–504. https://doi.org/10.1080/10705510701301834

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

Cohen, J. (1988). *Statistical power analysis for the behavioral sciences* (2nd ed.). Lawrence Erlbaum Associates.

Cope, B., Kalantzis, M., & Searsmith, D. (2021). Artificial intelligence for education: Knowledge and its assessment in AI-enabled learning ecologies. *Educational Philosophy and Theory*, *53*(12), 1229–1245. https://doi.org/10.1080/00131857.2020.1728732

Costello, A. B., & Osborne, J. W. (2005). Best practices in exploratory factor analysis: Four recommendations for getting the most from your analysis. *Practical Assessment, Research, and Evaluation*, *10*(7), 1–9. https://doi.org/10.7275/jyj1-4868

Creswell, J. W., & Clark, V. L. P. (2017). *Designing and conducting mixed methods research* (3rd ed.). SAGE Publications.

Creswell, J. W., & Creswell, J. D. (2018). *Research design: Qualitative, quantitative, and mixed methods approaches* (5th ed.). SAGE Publications.

Davis, F. D. (1989). Perceived usefulness, perceived ease of use, and user acceptance of information technology. *MIS Quarterly*, *13*(3), 319–340. https://doi.org/10.2307/249008

Davis, F. D., Bagozzi, R. P., & Warshaw, P. R. (1992). Extrinsic and intrinsic motivation to use computers in the workplace. *Journal of Applied Social Psychology*, *22*(14), 1111–1132. https://doi.org/10.1111/j.1559-1816.1992.tb00945.x

Deloitte. (2024). *State of generative AI in the enterprise* (2nd ed.) [Research Report]. Deloitte Insights. https://www.deloitte.com/insights/state-of-generative-ai

Deloitte. (2025). *AI readiness and human collaboration report 2025* [Research Report]. Deloitte Insights. https://www.deloitte.com/insights/ai-readiness-2025

DeVellis, R. F. (2016). *Scale development: Theory and applications* (4th ed.). SAGE Publications.

DeVellis, R. F., & Thorpe, C. T. (2021). *Scale development: Theory and applications* (5th ed.). SAGE Publications.

Fleming, S. M., & Dolan, R. J. (2012). The neural basis of metacognitive ability. *Philosophical Transactions of the Royal Society B*, *367*(1594), 1338–1349. https://doi.org/10.1098/rstb.2011.0417

Fornell, C., & Larcker, D. F. (1981). Evaluating structural equation models with unobservable variables and measurement error. *Journal of Marketing Research*, *18*(1), 39–50. https://doi.org/10.2307/3151312

Gartner. (2025). *How your CEO is thinking about AI: The rise of responsible AI leadership* [Executive Report]. Gartner. https://www.gartner.com/en/documents/how-your-ceo-is-thinking-about-ai-2025

Georgian & NewtonX. (2025). *AI benchmark 2025: Enterprise and growth-stage adoption trends* [Benchmark Report]. Georgian Partners. https://www.georgian.io/research/ai-benchmark-2025

Gursoy, D., Chi, O. H., Lu, L., & Nunkoo, R. (2019). Consumers acceptance of artificially intelligent (AI) device use in service delivery. *International Journal of Information Management*, *49*, 157–169. https://doi.org/10.1016/j.ijinfomgt.2019.03.008

Hair, J. F., Black, W. C., Babin, B. J., & Anderson, R. E. (2019). *Multivariate data analysis* (8th ed.). Cengage.

Henseler, J., Ringle, C. M., & Sarstedt, M. (2015). A new criterion for assessing discriminant validity in variance-based structural equation modeling. *Journal of the Academy of Marketing Science*, *43*(1), 115–135. https://doi.org/10.1007/s11747-014-0403-8

Hinkin, T. R. (1998). A brief tutorial on the development of measures for use in survey questionnaires. *Organizational Research Methods*, *1*(1), 104–121. https://doi.org/10.1177/109442819800100106

Holmes, W., Porayska-Pomsta, K., Holstein, K., Sutherland, E., Baker, T., Buckingham Shum, S., Santos, O. C., Rodrigo, M. T., Cukurova, M., Bittencourt, I. I., & Koedinger, K. R. (2022). Ethics of AI in education: Towards a community-wide framework. *International Journal of Artificial Intelligence in Education*, *32*, 504–526. https://doi.org/10.1007/s40593-021-00239-1

Horn, J. L. (1965). A rationale and test for the number of factors in factor analysis. *Psychometrika*, *30*(2), 179–185. https://doi.org/10.1007/BF02289447

Hu, L., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling*, *6*(1), 1–55. https://doi.org/10.1080/10705519909540118

IBM. (2023). *Global AI adoption index 2023: Enterprise trends and insights* [Survey Report]. IBM. https://newsroom.ibm.com/global-ai-adoption-index-2023

Igolkina, A. A., & Meshcheryakov, G. (2020). Semopy: A python package for structural equation modeling. In *Structural Equation Modeling: A Multidisciplinary Journal* (No. 6; Vol. 27, pp. 952–963) [Computer software]. https://doi.org/10.1080/10705511.2019.1704289

Information Services Group. (2025). *State of enterprise AI adoption report 2025* [Research Report]. ISG. https://www.isg-one.com/research/enterprise-ai-adoption-2025

Kasneci, E., Seßler, K., Küchemann, S., Bannert, M., Dementieva, D., Fischer, F., Gasser, U., Groh, G., Günnemann, S., Hüllermeier, E., Kruber, S., Kuber, G., Łapuschkin, S., Longo, L., Tüselmann, O., Welbers, C., & Zanker, M. (2023). ChatGPT for good? On opportunities and challenges of large language models for education. *Learning and Individual Differences*, *103*, 102274. https://doi.org/10.1016/j.lindif.2023.102274

Kaufman, L., & Rousseeuw, P. J. (2009). *Finding groups in data: An introduction to cluster analysis*. Wiley.

Kelly, S., Kaye, S.-A., & Oviedo-Trespalacios, O. (2023). What factors contribute to the acceptance

of artificial intelligence? A systematic review. *Telematics and Informatics*, *77*, 101925. https://doi.org/10.1016/j.tele.2022.101925

Kline, R. B. (2016). *Principles and practice of structural equation modeling* (4th ed.). Guilford Press.

Lakens, D. (2013). Calculating and reporting effect sizes to facilitate cumulative science: A practical primer for t-tests and ANOVAs. *Frontiers in Psychology*, *4*, 863. https://doi.org/10.3389/fpsyg.2013.00863

Lazar, J., & Stein, M. A. (2017). *Disability, human rights, and information technology*. University of Pennsylvania Press.

Lucidworks. (2025). *2025 generative AI global benchmark: Agentic systems and governance insights* [Benchmark Report]. Lucidworks. https://www.lucidworks.com/research/2025-generative-ai-benchmark

McGaugh, J. L. (2000). Memory—a century of consolidation. *Science*, *287*(5451), 248–251. https://doi.org/10.1126/science.287.5451.248

McKinsey & Company. (2023). *The state of AI in 2023: Generative AI's breakout year* [Survey Report]. McKinsey Global Institute. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-state-of-ai-in-2023

McKinsey & Company. (2024). *The state of AI in 2024: Generative AI's breakout year* [Survey Report]. McKinsey Global Institute. https://www.mckinsey.com/capabilities/quantumblack/our-insights/the-state-of-ai

McKinsey & Company. (2025). *The state of AI in 2025: Building the AI-powered organization* [Survey Report]. McKinsey Global Institute. https://www.mckinsey.com/capabilities/mckinsey-digital/our-insights/the-state-of-ai-in-2025

McKnight, D. H., Choudhury, V., & Kacmar, C. (2002). Developing and validating trust measures for e-commerce: An integrative typology. *Information Systems Research*, *13*(3), 334–359. https://doi.org/10.1287/isre.13.3.334.81

Meuter, M. L., Ostrom, A. L., Bitner, M. J., & Roundtree, R. (2003). The influence of technology

anxiety on consumer use and experiences with self-service technologies. *Journal of Business Research*, *56*(11), 899–906. https://doi.org/10.1016/S0148-2963(01)00276-4

Miller, E. K., & Cohen, J. D. (2001). An integrative theory of prefrontal cortex function. *Annual Review of Neuroscience*, *24*, 167–202. https://doi.org/10.1146/annurev.neuro.24.1.167

Milligan, G. W., & Cooper, M. C. (1985). An examination of procedures for determining the number of clusters in a data set. *Psychometrika*, *50*(2), 159–179. https://doi.org/10.1007/BF 02294245

MIT Media Lab. (2025). *The GenAI divide: State of enterprise AI in 2025* [Research Report]. MIT Media Lab. https://www.media.mit.edu/research/genai-divide-2025

Moore, G. C., & Benbasat, I. (1991). Development of an instrument to measure the perceptions of adopting an information technology innovation. *Information Systems Research*, *2*(3), 192–222. https://doi.org/10.1287/isre.2.3.192

Nunnally, J. C., & Bernstein, I. H. (1994). *Psychometric theory* (3rd ed.). McGraw-Hill.

OpenAI. (2023). GPT-4 technical report. *arXiv Preprint*. https://doi.org/10.48550/arXiv.2303.08 774

Packard, M. G., & Knowlton, B. J. (2002). Learning and memory functions of the basal ganglia. *Annual Review of Neuroscience*, *25*, 563–593. https://doi.org/10.1146/annurev.neuro.25.112 701.142937

Pedregosa, F., Varoquaux, G., Gramfort, A., Michel, V., Thirion, B., Grisel, O., Blondel, M., Prettenhofer, P., Weiss, R., Dubourg, V., Vanderplas, J., Passos, A., Cournapeau, D., Brucher, M., Perrot, M., & Duchesnay, É. (2011). Scikit-learn: Machine learning in python. In *Journal of Machine Learning Research* (Vol. 12, pp. 2825–2830) [Computer software].

Podsakoff, P. M., MacKenzie, S. B., Lee, J.-Y., & Podsakoff, N. P. (2003). Common method biases in behavioral research: A critical review of the literature and recommended remedies. *Journal of Applied Psychology*, *88*(5), 879–903. https://doi.org/10.1037/0021-9010.88.5.879

Preacher, K. J., & Hayes, A. F. (2008). Asymptotic and resampling strategies for assessing and comparing indirect effects in multiple mediator models. *Behavior Research Methods*, *40*(3),

879–891. https://doi.org/10.3758/BRM.40.3.879

Rogers, E. M. (2003). *Diffusion of innovations* (5th ed.). Free Press.

Shin, D. (2021). The effects of explainability and causability on perception, trust, and acceptance: Implications for explainable AI. *International Journal of Human-Computer Studies*, *146*, 102551. https://doi.org/10.1016/j.ijhcs.2020.102551

Siau, K., & Wang, W. (2018). Building trust in artificial intelligence, machine learning, and robotics. *Cutter Business Technology Journal*, *31*(2), 47–53.

Sporns, O. (2013). Network attributes for segregation and integration in the human brain. *Current Opinion in Neurobiology*, *23*(2), 162–171. https://doi.org/10.1016/j.conb.2012.11.015

Squire, L. R., & Kandel, E. R. (2009). *Memory: From mind to molecules* (2nd ed.). Roberts; Company.

Tabachnick, B. G., & Fidell, L. S. (2019). *Using multivariate statistics* (7th ed.). Pearson.

The pandas development team. (2020). *Pandas-dev/pandas: pandas* [Computer software]. Zenodo. https://doi.org/10.5281/zenodo.3509134

Trewin, S., Baez, M., Kocielnik, R., Introna, L., Holbrook, J., Terveen, L., Muller, M., Hurst, A., Shinohara, K., Morris, M. R., O'Leary, K., & Voida, A. (2019). AI fairness for people with disabilities: Point of view. *arXiv Preprint*. https://doi.org/10.48550/arXiv.1811.10670

Tulving, E. (2002). Episodic memory: From mind to brain. *Annual Review of Psychology*, *53*, 1–25. https://doi.org/10.1146/annurev.psych.53.100901.135114

Vallat, R. (2018). Pingouin: Statistics in python. In *Journal of Open Source Software* (No. 31; Vol. 3, p. 1026) [Computer software]. https://doi.org/10.21105/joss.01026

Vandenberg, R. J., & Lance, C. E. (2000). A review and synthesis of the measurement invariance literature: Suggestions, practices, and recommendations for organizational research. *Organizational Research Methods*, *3*(1), 4–70. https://doi.org/10.1177/109442810031002

Venkatesh, V. (2000). Determinants of perceived ease of use: Integrating control, intrinsic motivation, and emotion into the technology acceptance model. *Information Systems Research*, *11*(4), 342–365. https://doi.org/10.1287/isre.11.4.342.11872

Venkatesh, V. (2021). Adoption and use of AI tools: A research agenda grounded in UTAUT. *Annals of Operations Research*, 1–12. https://doi.org/10.1007/s10479-020-03918-9

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

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012b). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Venkatesh, V., Thong, J. Y. L., & Xu, X. (2012a). Consumer acceptance and use of information technology: Extending the unified theory of acceptance and use of technology. *MIS Quarterly*, *36*(1), 157–178. https://doi.org/10.2307/41410412

Virtanen, P., Gommers, R., Oliphant, T. E., Haberland, M., Reddy, T., Cournapeau, D., Burovski, E., Peterson, P., Weckesser, W., Bright, J., Walt, S. J. van der, Brett, M., Wilson, J., Millman, K. J., Mayorov, N., Nelson, A. R. J., Jones, E., Kern, R., Larson, E., … Mulbregt, P. van. (2020). SciPy 1.0: Fundamental algorithms for scientific computing in python. In *Nature Methods* (Vol. 17, pp. 261–272) [Computer software]. https://doi.org/10.1038/s41592-019-0686-2

Worthington, R. L., & Whittaker, T. A. (2006). Scale development research: A content analysis and recommendations for best practices. *The Counseling Psychologist*, *34*(6), 806–838. https://doi.org/10.1177/0011000006288127

Zawacki-Richter, O., Marín, V. I., Bond, M., & Gouverneur, F. (2019). Systematic review of research on artificial intelligence applications in higher education – where are the educators? *International Journal of Educational Technology in Higher Education*, *16*(39), 1–27. https://doi.org/10.1186/s41239-019-0171-0

Appendices

Appendix A: AI Readiness Scale (AIRS) Final 16-Item Instrument

The final validated 16-item AIRS instrument consists of eight constructs measured using a 7-point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree).

Performance Expectancy (PE)

1. **PE1**: I find AI tools useful in my work.

2. **PE2**: Using AI tools increases my productivity.

Effort Expectancy (EE)

3. **EE1**: AI tools are easy to use.

4. **EE2**: Learning to use AI tools is easy for me.

Social Influence (SI)

5. **SI1**: People who are important to me think I should use AI tools.

6. **SI2**: People who influence my behavior think I should use AI tools.

Facilitating Conditions (FC)

7. **FC1**: I have the resources necessary to use AI tools.

8. **FC2**: I have the knowledge necessary to use AI tools.

Hedonic Motivation (HM)

9. **HM1**: Using AI tools is fun.

10. **HM2**: Using AI tools is enjoyable.

Habit (HT)

11. **HT1**: The use of AI tools has become a habit for me.

12. **HT2**: I am addicted to using AI tools.

AI Trust (TR)

13. **TR1**: I trust the output generated by AI tools.

14. **TR2**: I believe AI tools are reliable.

AI Anxiety (ANX)

15. **ANX1**: I feel apprehensive about using AI tools.

16. **ANX2**: AI tools are somewhat intimidating to me.

Appendix B: Survey Materials

B.1 Participant Information Sheet

To be added.

B.2 Informed Consent Form

To be added.

B.3 Demographic Questions

To be added.

Appendix C: Supplementary Statistical Tables

C.1 Full Correlation Matrix

To be added.

C.2 Item-Level Descriptive Statistics

To be added.

C.3 Cross-Validation Results

To be added.

Appendix Z: AIRS Research Roadmap and Future Applications

This appendix outlines the research program envisioned to extend the validated AIRS instrument into practical organizational applications. The roadmap represents a multi-phase research agenda that builds systematically on the foundation established in this dissertation.

Z.1 Research Program Overview

The AI Readiness Scale (AIRS) validated in this dissertation represents Phase 0 of a comprehensive research program aimed at bridging the gap between AI adoption measurement and organizational AI maturity. The roadmap below outlines subsequent research phases, each requiring independent empirical validation.

Phase	Focus	Key Deliverables
Phase 0	Scale Validation	☐ This Dissertation: 8-factor, 16-item AIRS, structural model, user typology
Phase 1	Scoring System	AIRS Score algorithm, normative benchmarks, readiness classifications
Phase 2	Organizational Diagnostics	Team/org-level assessment, gap analysis, benchmarking protocols
Phase 3	Intervention Research	Segment-specific interventions, randomized trials, effectiveness validation
Phase 4	AI Readiness Ecosystem	Longitudinal tracking, industry adaptations, practitioner certification

Z.2 Phase 1: AIRS Score Development

Research Objective: Develop a scoring methodology that transforms raw AIRS responses into interpretable individual readiness scores with established normative benchmarks.

Key Research Questions:

- How should construct scores be weighted to optimize predictive validity?

- What normative distributions exist across student, professional, and leadership populations?

- What classification system best communicates readiness levels to practitioners?

Z.3 Phase 2: Organizational Diagnostics

Research Objective: Develop validated protocols for assessing AI readiness at team and organizational levels.

Key Research Questions:

- What aggregation methods preserve construct validity at organizational levels?
- Do organizational readiness profiles predict AI implementation success?
- What reporting formats maximize practitioner utility?

Z.4 Phase 3: Intervention Research

Research Objective: Design and empirically test segment-specific interventions based on the user typology framework.

The four-segment typology identified in this dissertation (AI Enthusiasts, Cautious Adopters, Moderate Users, Anxious Avoiders) suggests that different user populations may respond to different intervention approaches. Future research should employ randomized controlled trials to test whether segment-matched interventions outperform generic approaches.

Key Research Questions:

- Do segment-specific interventions outperform one-size-fits-all approaches?
- What intervention components drive segment-specific effectiveness?
- Do intervention effects persist over 6-12 month follow-up periods?

Z.5 Phase 4: Comprehensive AI Readiness Ecosystem

Research Objective: Develop an integrated system combining validated assessment, diagnostics, and intervention protocols.

Long-Term Vision:

- **Longitudinal Tracking**: Systems for monitoring organizational AI readiness progression

- **Industry Adaptations**: Validated modifications for healthcare, finance, education, and manufacturing contexts
- **Cross-Cultural Validation**: Replication across collectivist cultures, developing economies, and varying policy environments
- **Practitioner Resources**: Administration guides, interpretation frameworks, and training pathways

Z.6 Contribution to the Field

This research program addresses a critical gap in the technology adoption literature: while validated measurement instruments exist, the translation of assessment into organizational action remains underdeveloped. By systematically building from validated measurement through scoring, diagnostics, intervention, and ecosystem development, this roadmap offers a research-to-practice pipeline that can ultimately deliver the evidence-based tools organizations need to close the AI adoption-value gap.

Z.7 Collaboration and Licensing

The AIRS instrument validated in this dissertation is made available for academic research purposes. Organizations interested in applying the AIRS framework for organizational assessment should contact the author to discuss appropriate use, validation requirements, and potential research collaboration opportunities.

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