Artificial Intelligence Readiness Scale (AIRS): Dissertation Defense

Extending UTAUT2 for Enterprise AI Adoption

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December 2025

1 Slide 1: Title Slide

1.0.1 Artificial Intelligence Readiness Scale

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Dissertation Committee:

- Dr. Karina Kasztelnik (Chair)
- Dr. Jerome Jones
- Dr. Donna Day

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1.1 Slide 2: The AI Adoption Paradox

Organizations are adopting AI at unprecedented rates, but struggling to capture value.

The gap between AI adoption and value realization represents one of the most pressing challenges facing organizations today. Despite massive investment and enthusiasm, most AI initiatives fail to deliver measurable returns.

1.1.1 Chart Data: AI Adoption vs. Value Capture

Metric	Value	Source
Enterprise AI Adoption (2024)	72%	McKinsey
Enterprise AI Adoption (2025)	88%	McKinsey
Companies achieving measurable ROI	5%	BCG
GenAI pilots that fail to scale	90-95%	MIT Media Lab
"AI High Performers"	6%	McKinsey 2025

Key Insight: Adoption ≠ Value. Understanding the psychology behind this gap is critical.

1.2 Slide 3: Research Questions

This dissertation addresses the fundamental question: Why do people adopt (or resist) AI tools?

Traditional technology acceptance models like UTAUT have explained technology adoption for decades. But AI is different—it's opaque, probabilistic, and raises unique ethical concerns. Do our existing theories still apply?

Research Questions:

1. **RQ1**: Can we develop a psychometrically valid AI Readiness Scale extending UTAUT2?
2. **RQ2**: What factors most strongly predict AI adoption intention?
3. **RQ3**: Do traditional UTAUT predictors behave differently for AI?
4. **RQ4**: How do professional experience and population type moderate adoption?

1.3 Slide 4: Theoretical Foundation - UTAUT2

Building on 25+ years of technology acceptance research.

The Unified Theory of Acceptance and Use of Technology (UTAUT/UTAUT2) synthesizes decades of research into a unified framework that has been validated across thousands of studies. This dissertation extends this established foundation for the AI context.

UTAUT2 Core Constructs:

Construct	Definition	Meta-Analytic Effect (rc)
Performance Expectancy (PE)	Belief technology improves performance	.64 (strongest)
Effort Expectancy (EE)	Perceived ease of use	.51
Social Influence (SI)	Important others' opinions	.43
Facilitating Conditions (FC)	Organizational/technical support	.39
Hedonic Motivation (HM)	Enjoyment from use	.53
Price Value (PV)	Cost-benefit assessment	.52

Habit (HB)	Automaticity from repeated use	.66

Source: Blut et al. (2022) meta-analysis, Table 1: 737,112 users, 1,935 samples. rc = corrected correlation.

1.4 Slide 5: Why AI May Be Different

AI challenges fundamental assumptions of traditional acceptance models.

Unlike conventional software, AI systems operate through mechanisms that users cannot directly observe or verify. This opacity, combined with probabilistic outputs and ethical implications, may require theoretical extension.

Unique AI Characteristics:

Challenge	Traditional Tech	AI Systems
Transparency	Deterministic, observable	Opaque, “black box”
Outputs	Consistent, predictable	Probabilistic, variable
Errors	Traceable, fixable	Difficult to diagnose
Ethics	Minimal concern	Job displacement, bias, privacy
Trust basis	Reliability	Competence + integrity + benevolence

Proposed Extension: AI Trust (TR) as a new construct capturing trust in AI systems

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1.5 Slide 6: Research Design

A rigorous 10-phase psychometric validation approach.

This study employed a split-sample cross-validation design rarely used in scale development research. The development sample (n=261) was used for exploratory factor analysis, while the hold-out sample (n=262) provided independent confirmation.

Methodology Overview:

Phase	Analysis	Sample
1	Sample Split	N=523 -> 261/262
2	Exploratory Factor Analysis (EFA)	Development (n=261)
3	Confirmatory Factor Analysis (CFA)	Holdout (n=262)
4	Measurement Invariance	Student vs Professional
5	Structural Equation Modeling (SEM)	Full sample
6	Mediation Analysis	Full sample
7	Moderation Analysis	Experience, Population
8	Behavioral Validation	Tool usage correlation
9	Qualitative Analysis	Open-ended responses
10	Final Synthesis	Integration

1.6 Slide 7: Sample Characteristics

A diverse sample spanning the career development spectrum.

The sample of 523 U.S. adults includes students, individual contributors, managers, and executives—enabling examination of AI adoption across professional contexts and providing sufficient power for multi-group analyses.

Sample Demographics Chart Data:

Population	n	%
Students	216	41.3%
Professionals	184	35.2%
Leaders	123	23.5%
Total	**523**	**100%**

Additional Demographics:

Characteristic	Distribution
Education	Some college 35%, Bachelor’s 27%, HS/less 19%, Master’s 16%, Doctoral 3%
With Disability	13% (n=68)
AI Tool Users	89% use at least one AI tool

1.7 Slide 8: Instrument Validation Results

Excellent psychometric properties across all indices.

The 8-factor, 16-item AIRS instrument demonstrated exceptional model fit on the independent hold-out sample, exceeding all conventional thresholds. This provides strong evidence for the reliability and validity of the scale.

Model Fit Indices:

Index	Value	Threshold	Result
CFI	.975	$\geq .95$	[OK] Excellent
TLI	.960	$\geq .95$	[OK] Excellent
RMSEA	.065	$\leq .08$	[OK] Good
SRMR	.046	$\leq .08$	[OK] Excellent
χ^2/df	2.10	< 3.0	[OK] Excellent

Reliability Chart Data:

Construct	α	CR	AVE
Performance Expectancy	.803	.804	.673
Effort Expectancy	.859	.861	.756
Social Influence	.752	.763	.621
Facilitating Conditions	.743	.750	.601
Hedonic Motivation	.864	.865	.763
Price Value	.883	.883	.790
Habit	.909	.909	.833
AI Trust	.891	.891	.804

1.8 Slide 9: Constructs Excluded

Four AI-specific constructs failed to demonstrate adequate reliability.

An important finding of this research is that four proposed constructs—despite theoretical importance—could not be reliably measured with two-item scales. This represents a measurement challenge, not a theoretical failure, and guides future research.

Excluded Constructs:

Construct	Cronbach's α	Reason for Exclusion
Voluntariness (VO)	.406	Items measured choice vs. freedom—distinct dimensions
Explainability (EX)	.582	Items measured understanding vs. preference—distinct facets
Ethical Risk (ER)	.546	Items measured job displacement vs. privacy—distinct risk types
AI Anxiety (AX)	.301	Items measured avoidance vs. approach anxiety—distinct motivations

Implication: These constructs require 3-4 items per dimension for future operationalization. The theoretical importance remains; only the measurement proved insufficient.

1.9 Slide 10: KEY FINDING - Hypothesis Testing Results

Price Value, not Performance Expectancy, drives AI adoption.

This is the most striking finding of the dissertation. In traditional UTAUT research, Performance Expectancy is consistently the strongest predictor. For AI tools, users care more about whether AI is "worth it" than whether it's "useful."

Structural Model Results - Bar Chart Data:

Hypothesis	Path	β	p	Result
H1f	PV -> BI	**.505**	<.001	[OK] **STRONGEST**
H1e	HM -> BI	**.217**	.014	[OK] Supported
H1c	SI -> BI	**.136**	.024	[OK] Supported
H2	TR -> BI	.106	.064	[!] Marginal
H1d	FC -> BI	.059	.338	[X] Not Supported
H1g	HB -> BI	.023	.631	[X] Not Supported
H1b	EE -> BI	-.008	.875	[X] Not Supported
H1a	PE -> BI	-.028	.791	[X] Not Supported

Model R^2 = .852 (85.2% of variance explained, 8-factor diagnostic model)

1.10 Slide 11: Traditional Predictors Don't Work for AI

Performance Expectancy and Effort Expectancy, typically the strongest predictors, are non-significant for AI.

This finding challenges fundamental assumptions about technology adoption. In Blut et al.'s (2022) meta-analysis of 737,112 users, PE had the strongest effect (rc = .64). In our AI context, PE was essentially zero ($\beta = -.028$, $p = .791$).

1.10.1 Comparison Chart Data: Traditional UTAUT vs. AI Adoption

Construct	Meta-Analytic rc (Traditional)	AIRS β (AI)	Change
Performance Expectancy	.64	-.028	[DOWN] Collapsed
Effort Expectancy	.51	-.008	[DOWN] Collapsed
Price Value	.52	**.505**	[UP] Dominant
Hedonic Motivation	.53	.217	Similar
Social Influence	.43	.136	[DOWN] Reduced

Interpretation: For AI, utility is assumed or uncertain; users evaluate through a value lens ("Is it worth it?") rather than a utility lens ("Will it help me?").

1.11 Slide 12: What Drives AI Adoption?

Three factors significantly predict AI adoption intention.

The structural model reveals that AI adoption is driven primarily by cost-benefit perceptions, followed by intrinsic enjoyment and social influence. This pattern suggests organizations should lead with value propositions rather than capability demonstrations.

Significant Predictors (Ranked):

1. **Price Value ($\beta = .505$, $p < .001$)**: "Is the value worth the cost/effort?"
   - The cognitive trade-off between benefits received and resources invested
   - Includes time, learning curve, workflow disruption—not just money
2. **Hedonic Motivation ($\beta = .217$, $p = .014$)**: "Is it engaging and enjoyable?"
   - Intrinsic satisfaction from using AI tools
   - Curiosity and stimulation drive continued engagement
3. **Social Influence ($\beta = .136$, $p = .024$)**: "Do important others support AI use?"

- Peer influence and organizational norms
- AI champions and visible leadership matter

Near-Significant:

- AI Trust ($\beta = .106$, $p = .064$): Approaching significance, larger samples may confirm

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1.12 Slide 13: Experience Moderates Hedonic Motivation

As professionals gain experience, enjoyment matters more.

The moderation analysis revealed a significant interaction between professional experience and Hedonic Motivation. More experienced professionals weight intrinsic satisfaction more heavily when evaluating AI tools.

Experience Moderation Chart Data:

Interaction	β	p	Result
HM × Experience	**.136**	**.009**	[OK] Significant
PE × Experience	.112	.055	[!] Marginal
EE × Experience	.122	.161	[X] Not significant
TR × Experience	.081	.145	[X] Not significant

Interpretation: Early-career professionals may prioritize proving productivity; experienced professionals can afford to value enjoyment. This connects technology acceptance to career development theory in novel ways.

1.13 Slide 14: Population Differences

Students value enjoyment; Professionals value outcomes.

Multi-group analysis revealed significant population moderation for the Hedonic Motivation path. Students show a strong positive effect of enjoyment on adoption intention, while professionals show a negative effect.

Population Moderation Chart Data:

Path	Student β	Professional β	Δβ	p
HM -> BI	**+0.449**	-0.301	-0.750	**.041**
PV -> BI	+0.638	+0.808	+0.170	ns
SI -> BI	+0.007	+0.239	+0.232	ns
TR -> BI	-0.011	+0.153	+0.164	ns

Key Insight:

- **Students**: "Make it fun and I'll use it"
- **Professionals**: "Show me the value and I'll use it"

Different messaging strategies may be needed for different populations.

1.14 Slide 15: Four User Segments Identified

Cluster analysis reveals distinct adoption readiness profiles.

K-means clustering identified four user segments with distinct psychological profiles. This typology provides a framework for future research on tailored intervention strategies.

User Typology Chart Data:

Segment	n	%	Profile	Organizational Role
AI Enthusiasts	84	16%	High trust, high intention, low anxiety	Champions
Cautious Adopters	157	30%	High adoption but also high anxiety	Need reassurance
Moderate Users	191	37%	Neutral stance, average engagement	Can be influenced
Anxious Avoiders	91	17%	Low adoption, high anxiety	Need intervention

Cluster Centroids (Standardized):

Segment	PE (z)	Trust (z)	Anxiety (z)	Intention (z)
AI Enthusiasts	+1.42	+1.37	-0.86	+1.32
Cautious Adopters	+1.16	+0.86	+0.84	+0.88
Moderate Users	+0.26	+0.01	+0.42	-0.07
Anxious Avoiders	-1.16	-1.49	+0.76	-1.53

1.15 Slide 16: Behavioral Validation

Intentions strongly predict actual AI tool usage.

To validate the AIRS instrument against real behavior, we correlated Behavioral Intention with self-reported AI tool usage patterns. The strong correlation provides criterion validity evidence.

Validation Results:

Metric	Value
BI-Usage Correlation	$\rho = .69$, $p < .001$
Interpretation	Strong positive relationship

Tool Usage by Role (Effect Sizes):

Comparison	Cohen's d	Interpretation
Leaders vs. Students	1.14	Very large
Leaders vs. Professionals	0.74	Large
Professionals vs. Students	0.43	Medium

Key Insight: Organizational leaders demonstrate substantially higher AI tool usage, suggesting leadership engagement may be critical for organizational AI adoption.

1.16 Slide 17: Theoretical Contributions

Four primary contributions to technology acceptance theory.

This dissertation advances scholarly understanding of technology acceptance in the AI era, providing both theoretical extension and empirical evidence for context-specific modifications.

1.16.1 Contribution 1: UTAUT2 Extension for AI

- Demonstrated that traditional frameworks require modification for AI contexts
- AI Trust approaches significance, warranting further investigation

1.16.2 Contribution 2: Price Value Dominance

- First empirical evidence that PV > PE for AI adoption
- Challenges 25+ years of UTAUT findings where PE consistently dominates

1.16.3 Contribution 3: Career Development Integration

- Experience moderates HM effect ($p = .009$)
- Connects technology acceptance to vocational psychology

1.16.4 Contribution 4: User Typology Framework

- Four-segment model for adoption heterogeneity
- Foundation for future intervention research

1.17 Slide 18: Practical Implications

Evidence-informed recommendations for organizations.

While the cross-sectional design limits causal claims, the findings suggest several hypotheses for organizational practice that warrant experimental validation.

For AI Implementation:

Finding	Implication	Strategy
PV dominance (β=.505)	Lead with value, not features	Clear ROI demonstrations
HM significance (β=.217)	Design for engagement	Gamification, curiosity
SI significance (β=.136)	Leverage social proof	Champions, peer communities
PE non-significance	Don't assume utility sells	Focus on value proposition

For Different Populations:

Population	Priority	Approach
Students	Hedonic Motivation	Make it engaging and fun
Professionals	Price Value	Demonstrate clear ROI
Leaders	Already high adopters	Leverage as champions

1.18 Slide 19: Study Limitations

Important boundaries for interpretation.

As with all empirical research, these findings should be interpreted within the context of methodological limitations that guide future research directions.

Design Limitations:

Limitation	Impact	Mitigation
Cross-sectional design	Cannot establish causation	Longitudinal replication needed
Panel sampling	Limits generalizability	Topic-blinded recruitment via Centiment mitigates self-selection
Self-report measures	Common method variance	Behavioral validation included
U.S. only	Cultural specificity	International replication needed

Measurement Limitations:

Limitation	Impact	Future Direction
4 constructs dropped	Incomplete theoretical extension	3-4 items per dimension
2 items per construct	Minimal measurement	Expand to 3-4 items
Trust marginal (p=.064)	Underpowered for small effects	n > 600 recommended

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1.19 Slide 20: Future Research Agenda

A systematic roadmap from validated scale to organizational applications.

This dissertation establishes the validated AIRS instrument as a foundation for a multi-phase research program addressing the adoption-value gap.

Research Roadmap:

Phase	Focus	Status
Phase 0	AIRS Scale Validation	[OK] THIS DISSERTATION
Phase 1	AIRS Score Algorithm Development	Future Research
Phase 2	Diagnostic Protocol Development	Future Research
Phase 3	Intervention Framework Testing	Future Research
Phase 4	Comprehensive AI Readiness Ecosystem	Future Research

Immediate Research Priorities:

1. Replication with larger samples (n > 600) for small effect detection
2. Longitudinal design tracking intention -> behavior over 6-12 months
3. Redesign measures for excluded constructs (EX, ER, AX, VO)
4. Cross-cultural validation in collectivist cultures
5. Industry-specific adaptation studies

1.20 Slide 21: The Validated AIRS Instrument

A 16-item psychometrically sound scale for AI adoption research.

The final AIRS instrument consists of 8 constructs measured with 2 items each, using a 5-point Likert scale (1 = Strongly Disagree to 5 = Strongly Agree).

AIRS 16-Item Scale:

Construct	Item 1	Item 2
PE	AI tools help me accomplish tasks more quickly	Using AI improves the quality of my work
EE	Learning to use AI tools is easy for me	Interacting with AI tools is clear and understandable

Construct	Item 1	Item 2
SI	People whose opinions I value encourage AI use	Leaders in my organization support AI use
FC	I have access to training for AI tools	AI tools are compatible with other systems I use
HM	Using AI tools is stimulating and engaging	AI tools make my work more interesting
PV	I get more value from AI than the effort required	Using AI is worth the learning curve
HB	Using AI tools has become a habit for me	I tend to rely on AI tools by default
TR	I trust AI tools to provide reliable information	I trust the AI tools available to me

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1.21 Slide 22: Key Takeaways

What we learned about AI adoption psychology.

This dissertation provides empirical evidence that AI represents a psychologically distinct technology category, requiring modified theoretical frameworks and differentiated organizational strategies.

Five Key Findings:

1. **Price Value dominates** ($\beta = .505$) — Users evaluate AI through a value lens, not a utility lens
2. **Performance Expectancy collapses** ($\beta = -.028$, ns) — Traditional utility assumptions don't apply to AI
3. **Experience moderates enjoyment** ($p = .007$) — Career development connects to technology acceptance
4. **Four user segments exist** — Heterogeneous adoption readiness requires tailored approaches
5. **The AIRS instrument is validated** — CFI = .975, $R^2 = .861$, strong psychometric properties

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1.22 Slide 23: Conclusion

Bridging the gap between AI adoption and value realization.

As AI transforms professional work, understanding adoption psychology becomes critical. This dissertation establishes that AI adoption operates through different mechanisms than previous technology adoption, with cost-benefit perceptions and intrinsic enjoyment mattering more than conventional utility considerations.

Summary Statement:

The validated AIRS instrument provides researchers with a psychometrically sound foundation for investigating AI adoption. The finding that Price Value—not Performance Expectancy—dominates AI adoption intention represents a significant theoretical departure that challenges fundamental assumptions about technology acceptance.

Organizations seeking to close the adoption-value gap should focus on demonstrating clear return on investment, designing engaging user experiences, and leveraging social influence through visible AI champions.

Final Thought: Understanding why people adopt AI is the first step toward ensuring AI adoption creates genuine value.

1.23 Slide 24: Questions & Discussion

Thank you for your attention.

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- LinkedIn: [your profile]
- GitHub: github.com/fabioc-aloha/AIRS_Data_Analysis

Resources:

- Full dissertation available upon request
- AIRS instrument available for research use (CC BY 4.0)
- Analysis notebooks: Open source (MIT License)

1.24 Appendix Slides

1.24.1 Appendix A: Data Retention & Ethics

1.24.1.1 IRB Approval and Data Protection This research was conducted with full IRB approval, ensuring ethical treatment of participants and proper data handling throughout the study.

Ethics Summary:

Aspect	Details
IRB Status	Approved (Exempt Category 2)
Consent	Electronic informed consent obtained
PII Collected	None (no names, emails, IP addresses)
Data Format	Anonymized, de-identified
Retention Period	Until January 2028 (3 years per 45 CFR 46)
Public Availability	GitHub repository (MIT/CC BY 4.0 licenses)

Data Access:

- **Repository**: github.com/fabioc-aloha/AIRS_Data_Analysis
- **Data File**: data/AIRS_clean.csv (N=523)
- **Analysis**: 10 Jupyter notebooks, fully reproducible
- **Thesis**: Complete dissertation in Markdown + PDF

1.24.2 Appendix B: Complete Hypothesis Summary

#	Hypothesis	β	p	Result
H1a	PE -> BI	-.028	.791	[X] Not Supported
H1b	EE -> BI	-.008	.875	[X] Not Supported
H1c	SI -> BI	.136	.024	[OK] Supported
H1d	FC -> BI	.059	.338	[X] Not Supported
H1e	HM -> BI	.217	.014	[OK] Supported
H1f	PV -> BI	.505	<.001	[OK] Supported (Strongest)
H1g	HB -> BI	.023	.631	[X] Not Supported
H2	TR -> BI	.106	.064	[!] Marginal
H3	AIRS > UTAUT2	ΔAIC +2.01	—	[X] Not Supported
H4	BI ↔ Usage	ρ = .69	<.001	[OK] Supported

Summary: 3/7 UTAUT paths supported, Trust marginal, Behavioral validation confirmed

1.24.3 Appendix C: Model Fit Comparison

Model	Factors	Items	CFI	TLI	RMSEA	SRMR	Selected
A	7	21	.938	.923	.078	.058	No
B	8	20	.952	.940	.070	.052	No
C	8	18	.964	.953	.066	.048	No
D	**8**	**16**	**.975**	**.960**	**.065**	**.046**	**Yes**

1.24.4 Appendix D: Bibliography Highlights

- **92 references** spanning technology acceptance, AI adoption, scale development, and psychometrics
- Key foundational sources:
  - Venkatesh et al. (2003, 2012) — UTAUT/UTAUT2
  - Blut et al. (2022) — UTAUT meta-analysis
  - Hair et al. (2019) — Multivariate data analysis
  - DeVellis & Thorpe (2021) — Scale development
- Industry sources:
  - McKinsey State of AI (2024, 2025)
  - BCG AI Adoption (2024, 2025)
  - MIT Media Lab NANDA Initiative
