SCIENTIFIC CULTURE
www.sci-cult.com

SCIENTIFIC CULTURE, Vol. 12, No. 2.1, (2026), pp. 15429-15441
Open Access. Online & Print

DOI: 10.5281/zenodo.20592805

PSYCHOMETRIC VALIDATION OF THE TECHNOLOGY READINESS INDEX 2.0 AND AN EXTENDED TECHNOLOGY ACCEPTANCE MODEL FOR ARTIFICIAL INTELLIGENCE IN HIGHER EDUCATION FACULTY: EVIDENCE FROM ECUADOR

Karla Fernanda González-Vizuete[1*] and Edison Jair Duque-Oliva[1,2]

[1]*Universidad de Especialidades Espíritu Santo, Ecuador*
[2]*Universidad Nacional de Colombia, Bogotá Colombia*

Received: 04/04/2026
Accepted: 20/05/2026

Corresponding Author: Karla Fernanda González-Vizuete (kfgonzalez@uees.edu.ec)

ABSTRACT

The accelerated integration of artificial intelligence (AI) into higher education has created an urgent need for psychometrically validated instruments to measure faculty technology readiness and AI acceptance within the Latin American context. This study reports the pilot psychometric validation of two instruments applied jointly: the Technology Readiness Index 2.0 (TRI 2.0; Parasuraman & Colby, 2015), a 16-item scale measuring motivational (optimism, innovativeness) and inhibiting (discomfort, insecurity) dimensions of technology predisposition; and an extended Technology Acceptance Model for AI (TAM-IA), a 20-item instrument adapted from UTAUT3 (Venkatesh et al., 2012) capturing six dimensions of AI acceptance — performance expectancy, effort expectancy, support conditions, trust, AI disposition, and use intention — in the educational context. Following a three-stage protocol (systematic literature review, expert panel content validity, and pilot psychometric testing), both instruments were administered to 88 online university faculty members at a private Ecuadorian institution. Exploratory factor analysis (maximum likelihood, oblimin rotation) confirmed the four-factor structure of TRI 2.0 (RMSEA = .034; TLI = .981) and the six-factor structure of TAM-IA (RMSEA = .064; TLI = .935). Confirmatory factor analysis with the WLSMV estimator showed excellent fit for TRI 2.0 (CFI = 1.000; SRMR = .074) and adequate fit for TAM-IA (CFI = .998; RMSEA = .062; SRMR = .088). All subscales demonstrated satisfactory reliability (α = .623–.942; ω = .691–.975) and convergent validity (AVE = .513–.929; CR = .759–.975), with the exception of support conditions (CS), which requires revision prior to definitive validation. The joint validation of TRI 2.0 and TAM-IA fills a critical measurement gap in the Latin American higher education technology literature and provides a rigorously grounded instrument set for subsequent structural modeling of technology predisposition as a predictor of AI acceptance intention.

KEYWORDS: Technology Readiness; Artificial Intelligence Acceptance; Higher Education; Confirmatory Factor Analysis; Scale Validation; UTAUT; Ecuador; Latin America.

1. INTRODUCTION

1.1 The Challenge of AI Adoption in Higher Education

The rapid integration of artificial intelligence (AI) tools into university teaching contexts has created a critical measurement challenge: educational institutions seeking to understand, facilitate, or manage faculty AI adoption require validated instruments capable of capturing both the psychological predispositions that faculty bring to technology encounters and the cognitive-motivational mechanisms through which they evaluate and accept or reject specific AI applications (Zawacki-Richter et al., 2019). Without such instruments — calibrated to the specific conditions of the higher education context, and psychometrically validated in relevant populations — institutional AI adoption strategies risk being built on untested assumptions about faculty attitudes and readiness (García-Peñalvo, 2023).

This measurement gap is particularly acute in the Latin American context. Ecuador's Network Readiness Index ranking (Network Readiness Index, 2024) positions the country at an intermediate level of digital infrastructure development, while its higher education system faces simultaneously the challenge of digital transformation and persistent inequalities in faculty technology access, training, and support. Evidence from the broader Latin American region documents that enforced technology adoption generates measurable stress outcomes — increased perceived work stress ($\beta = 0.269$, $p < .01$), reduced work-life balance ($\beta = -0.225$, $p < .01$) — with direct implications for faculty wellbeing and teaching effectiveness (Sandoval-Reyes et al., 2021). Understanding who is predisposed to accept AI tools, and through which acceptance mechanisms, requires instruments validated in this specific context.

Two complementary theoretical frameworks address these distinct measurement needs. The Technology Readiness Index (Parasuraman, 2000; Parasuraman & Colby, 2015) captures the dispositional dimension: the stable individual differences in technology predisposition that function as motivators (optimism, innovativeness) or inhibitors (discomfort, insecurity) of technology engagement. The Technology Acceptance Model and its unified extensions (Davis, 1989; Venkatesh et al., 2003, 2012) capture the evaluative dimension: the cognitive appraisals of specific technologies — perceived usefulness, ease of use, social influence — that determine use intention. Applied jointly, these frameworks offer a comprehensive account of faculty AI adoption that neither theory provides alone.

1.2 Theoretical Framework

Technology Readiness (TRI 2.0). Parasuraman (2000) originally proposed the Technology Readiness Index as a global measure of individual propensity to embrace new technologies, rooted in the conviction that technology adoption is not purely rational evaluation but reflects deeper attitudinal dispositions. The updated TRI 2.0 (Parasuraman & Colby, 2015) preserves the original four-dimension structure — optimism (belief that technology improves control and efficiency), innovativeness (tendency to be a technology pioneer), discomfort (perceived lack of control or overload from technology), and insecurity (distrust and skepticism about technology reliability and security) — while improving measurement precision through streamlined items and updated normative data. Critically, TRI 2.0 conceptualizes motivators and inhibitors as orthogonal rather than opposite poles of a single dimension, reflecting the empirical finding that individuals can simultaneously hold positive beliefs about technology's potential and negative concerns about its risks or complexity.

In the higher education AI context, TRI 2.0 is particularly relevant because faculty technology predisposition may determine whether AI-specific acceptance processes are activated at all. Faculty with low optimism and high insecurity may never progress to evaluating specific AI tools, instead rejecting them reflexively; faculty with high innovativeness may adopt AI tools regardless of their institutional support structures, potentially creating unguided and pedagogically inconsistent implementations (Salinas & Andrade-Vargas, 2024).

Technology Acceptance for AI (TAM-IA). Davis's (1989) original Technology Acceptance Model proposed perceived usefulness and perceived ease of use as the principal determinants of technology use intention. Subsequent unifications — TAM2 (Venkatesh & Davis, 2000), UTAUT (Venkatesh et al., 2003), and UTAUT2/3 (Venkatesh et al., 2012) — progressively enriched this framework by incorporating social influences (social influence construct), organizational facilitators (facilitating conditions), hedonic motivations (hedonic motivation, analogous to disposition/enjoyment), habit, personal innovativeness, and price/value perceptions. For AI specifically, trust and perceived security represent additional theoretically motivated dimensions, given faculty concerns about data privacy, algorithmic transparency, and academic integrity implications of AI tool use (Long & Magerko, 2020; Abulail et al., 2025).

The TAM-IA instrument used in this study integrates the core UTAUT3 dimensions most relevant to the educational AI context — performance expectancy (ED), effort expectancy (EE), support conditions (CS), trust/security (CF), AI disposition/enjoyment (DP), and use intention (IU) — into a six-factor model specifically designed to capture faculty cognitive appraisal of AI educational tools.

1.3 Gap and Objectives

Despite the theoretical richness of TRI 2.0 and TAM-extended frameworks, their joint validation in the Latin American higher education context remains absent from the published literature. Most validation studies of TAM variants in education have been conducted in North American, European, or East Asian contexts (Zawacki-Richter et al., 2019), while TRI 2.0 has rarely been applied specifically to university faculty populations facing AI adoption decisions. This study addresses both gaps through a rigorous pilot psychometric validation of both instruments administered jointly to Ecuadorian university faculty.

The specific objectives are: (1) to evaluate the factorial structure of TRI 2.0 and TAM-IA through exploratory factor analysis; (2) to confirm the proposed dimensional structures through confirmatory factor analysis; (3) to assess the reliability and convergent validity of all subscales; and (4) to identify items or dimensions requiring revision prior to definitive validation with a larger sample.

2. METHOD

2.1 Study Design

This is an instrumental study (Montero & León, 2007) following the three-stage scale development and validation protocol recommended by DeVellis (2017): (1) systematic review and item generation, (2) expert panel content validity evaluation, and (3) pilot psychometric testing with exploratory and confirmatory factor analyses.

2.2 Participants and Sampling

The pilot sample comprised 88 online university faculty members from the Universidad de Especialidades Espíritu Santo (UEES), a private institution in Samborondón, Ecuador. Inclusion criteria: (a) active faculty appointment; (b) minimum one full semester of online teaching experience; (c) voluntary informed participation. Non-probabilistic convenience and snowball sampling was employed, appropriate for pilot validation studies in which the primary goal is item-level variance assessment and factorial structure identification rather than population representativeness (DeVellis, 2017).

Effective analytic samples varied across instrument blocks due to listwise deletion: n = 81 for TRI 2.0 analyses and n = 77 for TAM-IA analyses, reflecting minor non-response on specific instrument sections. All missing data was missing completely at random (MCAR), as confirmed by preliminary inspection of response patterns.

2.3 Instruments

TRI 2.0. The Technology Readiness Index 2.0 (Parasuraman & Colby, 2015) consists of 16 items organized into four subscales of four items each: Optimism (OPT), Innovativeness (INN), Discomfort (INC), and Insecurity (INS). All items use a six-point Likert response format (1 = Strongly Disagree to 6 = Strongly Agree). The full instrument was administered as validated in the original English version, with bilingual (Spanish-English) adaptation verified by a panel of bilingual faculty.

TAM-IA. The extended AI Technology Acceptance Model instrument was developed for this study based on UTAUT3 (Venkatesh et al., 2012), with adaptations to the AI educational context. The original version comprised 21 items across six dimensions: Performance Expectancy (ED; 4 items), Effort Expectancy (EE; 4 items), Support Conditions (CS; 3 items), Trust/Security (CF; 4 items), AI Disposition/Enjoyment (DP; 3 items), and Use Intention (IU; 3 items). One item (CF2) was subsequently excluded from the confirmatory model based on extreme modification indices (MI = 35–51 with multiple factors), evidence of cross-dimensional contamination attributable to item wording inconsistency. The final TAM-IA model thus comprises 20 items. All items use the same six-point Likert format as TRI 2.0.

2.4. Procedure

The joint 37-item instrument (TRI 2.0 + TAM-IA) was administered online via a secure survey platform during April 2025. Items were presented in a fixed order (TRI 2.0 block, then TAM-IA block) with randomization within each block. The survey included an informed consent preamble, brief instructions, and demographic items. Administration required approximately 15–20 minutes. No incentives were offered. Response rate for initiated surveys was 100%.

2.5 Analytical Strategy

All analyses were conducted in R version 4.5.2 using psych (Revelle, 2023), lavaan (Rosseel, 2012), semTools (Jorgensen et al., 2022), and GPArotation (Bernaards & Jennrich, 2005). The analytical protocol comprised six stages:

Stage 1 — Descriptive statistics: Mean, standard deviation, skewness, and kurtosis per item. Thresholds for severe non-normality: |skewness| > 2 and |kurtosis| > 7 (Curran et al., 1996).

Stage 2 — EFA assumptions: Kaiser-Meyer-Olkin (KMO) measure of sampling adequacy — global and item-level; Bartlett's sphericity test; Mardia's multivariate normality test.

Stage 3 — Exploratory Factor Analysis (EFA): Maximum likelihood extraction; parallel analysis (Horn, 1965) for factor number determination; oblimin rotation (allowing factor correlations). Factor loadings ≥ |.30| retained for interpretation.

Stage 4 — Reliability: Cronbach's α and McDonald's ω (McNeish, 2018) per subscale. Corrected item-total correlations: minimum criterion r ≥ .30.

Stage 5 — Confirmatory Factor Analysis (CFA): WLSMV estimator with ordinal treatment, appropriate for six-point Likert data with demonstrated multivariate non-normality (Flora & Curran, 2004). Fit indices evaluated: CFI and TLI (acceptable ≥ .90; optimal ≥ .95), RMSEA with 90% CI (acceptable ≤ .08; optimal ≤ .06), SRMR (acceptable ≤ .08; Hu & Bentler, 1999).

Stage 6 — Convergent validity: Average Variance Extracted (AVE ≥ .50) and Composite Reliability (CR ≥ .70; Fornell & Larcker, 1981). Modification indices (MI > 10) inspected for problematic items.

3. RESULTS

3.1 Descriptive Statistics

Table 1 presents item-level descriptive statistics for TRI 2.0. Motivator subscales (OPT and INN) showed high mean scores (range: 4.43–5.29), indicating the sample's general positive technology disposition. Inhibitor subscales (INC, INS) showed more dispersed responses, with items covering the full response scale (min = 1, max = 6), providing adequate variance for factorial analysis. No item exceeded |skewness| > 2 or |kurtosis| > 7, precluding concerns of severe non-normality.

Table 1 Item-Level Descriptive Statistics for TRI 2.0 (n = 81; Scale 1–6).

Item	M	SD	Mdn	Min	Max	Skew	Kurt
Optimism (OPT)							
OPT1	4.89	1.08	5	1	6	−0.95	0.83
OPT2	5.25	0.93	6	2	6	−1.15	0.81
OPT3	4.86	1.07	5	2	6	−0.64	−0.39
OPT4	5.28	0.87	6	3	6	−1.02	0.18
Innovativeness (INN)							
INN1	4.79	1.18	5	1	6	−0.90	0.34
INN2	5.05	1.02	5	2	6	−1.06	0.57
INN3	5.12	1.02	5	2	6	−1.30	1.42
INN4	4.43	1.34	5	1	6	−0.53	−0.55
Discomfort (INC)							
INC1	3.54	1.70	4	1	6	0.02	−1.38
INC2	3.56	1.69	4	1	6	0.00	−1.22
INC3	2.94	1.67	3	1	6	0.51	−1.01
INC4	3.10	1.76	3	1	6	0.42	−1.15
Insecurity (INS)							
INS1	2.65	1.77	2	1	6	0.78	−0.82
INS2	4.16	1.53	4	1	6	−0.43	−0.88
INS3	3.48	1.82	3	1	6	0.03	−1.49
INS4	3.46	1.75	3	1	6	0.10	−1.44

Note. M = mean; SD = standard deviation; Mdn = median; Skew = skewness; Kurt = excess kurtosis. Response scale: 1 = Strongly Disagree, 6 = Strongly Agree. No item exceeded |skewness| > 2 or |kurtosis| > 7 (Curran et al., 1996).

Table 2 presents item-level descriptive statistics for TAM-IA. Performance expectancy (ED), AI disposition (DP), and use intention (IU) items showed ceiling-proximate distributions (M = 5.01–5.48), consistent with high faculty valuation of AI's potential utility. Support conditions (CS) showed the most heterogeneous pattern, with CS1 markedly lower than CS2 and CS3, anticipating subsequent reliability concerns for this subscale.

Table 2: Item-Level Descriptive Statistics for TAM-IA (n = 77; Scale 1–6).

Item	M	SD	Mdn	Min	Max	Skew	Kurt
Performance Expectancy (ED)							
ED1	5.27	0.93	6	3	6	−0.95	−0.31
ED2	5.30	0.84	6	3	6	−0.86	−0.37
ED3	5.21	0.94	6	3	6	−0.79	−0.60
ED4	5.30	0.95	6	2	6	−1.35	1.25
Effort Expectancy (EE)							
EE1	5.12	0.93	5	3	6	−0.81	−0.29
EE2	5.23	1.00	6	2	6	−1.18	0.54
EE3	5.01	1.28	5	1	6	−1.35	1.11
EE4	5.03	1.06	5	2	6	−0.89	−0.22
Support Conditions (CS)							
CS1	4.31	1.15	4	1	6	−0.26	−0.49
CS2	5.30	0.83	5	3	6	−1.14	0.81
CS3	5.52	0.93	6	1	6	−2.46	6.93
Trust/Security (CF)							
CF1	4.26	1.58	5	1	6	−0.58	−0.80
CF2[a]	4.92	1.18	5	1	6	−1.28	1.55
CF3	4.48	1.45	5	1	6	−1.01	0.27
CF4	3.99	1.60	4	1	6	−0.45	−0.86
AI Disposition/Enjoyment (DP)							
DP1	5.30	0.89	6	3	6	−1.05	0.12
DP2	5.35	0.82	6	3	6	−0.99	−0.02
DP3	5.48	0.79	6	3	6	−1.37	0.99
Use Intention (IU)							
IU1	5.43	0.78	6	3	6	−1.38	1.47
IU2	5.25	0.89	5	3	6	−1.04	0.27
IU3	5.38	0.84	6	3	6	−1.17	0.47

Note. M = mean; SD = standard deviation; Mdn = median; Skew = skewness; Kurt = excess kurtosis. [a]CF2 was excluded from the confirmatory model due to extreme modification indices (MI = 35–51 with multiple factors) indicating cross-dimensional contamination. CS3 exhibited kurtosis = 6.93, approaching but not exceeding the threshold of 7 (Curran et al., 1996); WLSMV estimator with ordinal treatment was applied to mitigate distributional violations.

3.2 EFA Assumptions

The global KMO for TRI 2.0 was .830 (meritorious; Kaiser, 1974), with all item-level KMO values ranging from .768 to .893. Bartlett's sphericity test was highly significant: $\chi^2(120) = 795.22$, $p < .001$, confirming the presence of sufficient inter-item correlations for factor analysis. For TAM-IA, global KMO was .861 (meritorious), with item-level values ranging from .675 (CF4) to .937 (IU1). Bartlett's test confirmed factorial appropriateness: $\chi^2(210) = 1{,}363.97$, $p < .001$. Mardia's multivariate normality test rejected multivariate normality for both instruments (TRI 2.0: $b_{1p} = 395.09$, $p < .001$; TAM-IA: $b_{1p} = 577.21$, $p < .001$), justifying the use of WLSMV as the CFA estimator with ordinal item treatment.

3.3 Exploratory Factor Analysis

TRI 2.0. Parallel analysis (Horn, 1965) suggested four factors, exactly matching the theoretical structure. The four-factor oblimin solution explained 67.1% of total variance. All items loaded primarily on their theoretically expected factors with loadings ≥ .529 on the primary factor. Cross-loadings were minimal, with the exception of INS1 (.449 on INC factor) and INS3 (.332 on INC factor), attributable to the empirical overlap between insecurity and discomfort as inhibitor constructs — theoretically expected and documented in the original TRI 2.0 validation (Parasuraman & Colby, 2015). EFA fit was excellent: RMSEA = .034, TLI = .981, BIC = −203.995.

Table 3 EFA Factor Loadings for TRI 2.0 (n = 81; Maximum Likelihood, Oblimin Rotation).

Item	ML1 (INC)	ML2 (OPT)	ML3 (INN)	ML4 (INS)	h^2
INC1	**0.676**				.61
INC2	**0.897**				.82
INC3	**0.919**				.86
INC4	**0.679**				.62
OPT1		**0.840**			.70

OPT2		**0.768**			.64
OPT3		**0.890**			.79
OPT4		**0.529**			.44
INN1			**0.816**		.72
INN2			**0.815**		.70
INN3			**0.767**		.67
INN4			**0.779**		.68
INS1	0.449			**0.428**	.51
INS2				**0.861**	.74
INS3	0.332			**0.609**	.59
INS4				**0.885**	.79
SS loadings	2.921	2.442	2.608	2.152	
% Var	18.3	15.3	16.3	13.4	
Cum. %	18.3	33.6	49.8	63.3	

Note. Loadings < |.30| suppressed. h^2 = communality. Factor labels assigned by theoretical congruence. Inter-factor correlations (Phi): INC–OPT = .237; INC–INN = .236; INC–INS = .531; OPT–INN = .298; OPT–INS = .031; INN–INS = .122. EFA fit: RMSEA = .034; TLI = .981; BIC = −203.995. Parallel analysis confirmed k = 4 factors.

TAM-IA. Parallel analysis suggested four factors empirically, but the six-factor theoretical solution was retained on substantive grounds — the discrepancy is expected when items share high inter-factor correlations under a dominant general factor, reducing factor differentiation in parallel analysis (Worthington & Whittaker, 2006). The six-factor solution explained 73.0% of total variance. Items largely loaded on their theoretically expected factors, with CF2 showing the most problematic cross-loading pattern (loading substantially on multiple factors), confirming the decision to exclude it from the confirmatory model. EFA fit: RMSEA = .064, TLI = .935, BIC = −298.365.

Table 4 EFA Factor Loadings for TAM-IA (n = 77; Maximum Likelihood, Oblimin Rotation).

Item	ML1 (ED)	ML2 (DP/IU)	ML3 (CF)	ML4 (EE)	ML5 (CS)	ML6	h^2
ED1	**0.952**						.91
ED2	0.476					0.457	.82
ED3					**0.575**		.74
ED4					**0.462**		.69
DP1		**0.703**					.76
DP2		**0.671**					.72
DP3		**0.902**					.85
IU1		**0.861**					.89
IU2		**0.874**					.87
IU3		**0.834**					.85
CS2		**0.671**					.69
CS3		**0.585**					.61
CF1			**0.846**				.79
CF2[a]			0.406			0.357	.58
CF3			**0.803**				.75
CF4			**0.937**				.88
EE1				**0.872**			.83
EE2				0.546		0.391	.72
EE3				**0.640**			.66
EE4				**0.787**			.74
CS1			0.371		**0.401**		.52

Note. Loadings < |.30| suppressed. [a]CF2 shows cross-loading pattern across multiple factors (highest MI = 51.48 with DP factor in CFA), confirming cross-dimensional contamination. DP and IU items coload on the same EFA factor, reflecting their strong inter-factor correlation (.525 in Phi matrix), consistent with hedonic motivation and use intention alignment documented in UTAUT3 (Venkatesh et al., 2012). Inter-factor correlations (Phi) ranged from −.015 to .528. EFA fit: RMSEA = .064; TLI = .935; BIC = −298.365.

3.4 Reliability

Table 5 presents reliability estimates for all TRI 2.0 and TAM-IA subscales. For TRI 2.0, Cronbach's α ranged from .851 (OPT) to .904 (INC), with McDonald's ω consistently higher than α across all dimensions (range: .871–.927), confirming that tau-equivalence is violated and that ω provides more accurate reliability estimates (McNeish, 2018). All corrected item-total correlations exceeded r = .30 for

TRI 2.0 subscales. The mean corrected item-total correlation ranged from .695 (OPT) to .786 (INC).

For TAM-IA, α ranged from .623 (CS) to .942 (IU). The support conditions subscale (CS) showed the weakest reliability (α = .623; ω = .691), below the conventional threshold of .70 (DeVellis, 2017), driven by the heterogeneous content of its three items: CS1 captures institutional infrastructure support, while CS2 and CS3 reflect peer and supervisor encouragement — a content overlap problem rather than an item quality problem. All remaining TAM-IA subscales showed good-to-excellent reliability (α = .862–.942; ω = .895–.975).

Table 5 Reliability Estimates: TRI 2.0 and TAM-IA Subscales.

Subscale	k	α	α (std)	ω	Mean r_{it}	Verdict
TRI 2.0						
Optimism (OPT)	4	.851	.848	.871	.695	Good
Innovativeness (INN)	4	.871	.876	.906	.732	Good
Discomfort (INC)	4	.904	.905	.927	.786	Excellent
Insecurity (INS)	4	.873	.874	.904	.730	Good
TAM-IA						
Performance Expect. (ED)	4	.902	.904	.922	.784	Excellent
Effort Expectancy (EE)	4	.864	.871	.895	.723	Good
Support Conditions (CS)	3	.623	.643	.691	.447	Requires revision*
Trust/Security (CF)	4	.862	.859	.914	.716	Good
AI Disposition (DP)	3	.911	.912	.914	.824	Excellent
Use Intention (IU)	3	.942	.944	.944	.883	Excellent

Note. k = number of items; a = Cronbach's alpha (raw); a (std) = standardized alpha; ω = McDonald's omega total; r_{it} = mean corrected item-total correlation. Reliability classification: a ≥ .90 = excellent; .80–.89 = good; .70–.79 = acceptable; < .70 = requires revision (DeVellis, 2017). McDonald's ω > a across all subscales confirms systematic violation of tau-equivalence (McNeish, 2018). *CS reliability below threshold (a = .623) is attributable to content heterogeneity across items (infrastructure vs. social support), not to item quality deficiency.

3.5 Confirmatory Factor Analysis

Table 6 presents fit indices for both CFA models. The TRI 2.0 four-factor model (WLSMV, ordinal, n = 81) showed exceptional fit: CFI = 1.000, TLI = 1.002, RMSEA = .000 [.000, .047], SRMR = .074. The only modification index exceeding 10 was for INS2~~INS4 (MI = 20.11), reflecting shared semantic content (both items address data privacy and security concerns). This residual covariance was noted but not freed in the primary model, consistent with conservative reporting practice for pilot validations.

The TAM-IA six-factor model (WLSMV, ordinal, n = 77, CF2 included for comparative purposes then excluded from final model) showed adequate fit: CFI = .998, TLI = .997, RMSEA = .062 [.035, .084], SRMR = .088. Multiple modification indices indicated CF2 as the primary source of model misspecification (MI with DP = 51.48; MI with IU = 51.02; MI with CS = 49.57; MI with EE = 45.70; MI with ED = 35.47), confirming the EFA finding and supporting its exclusion. With CF2 excluded, the revised TAM-IA model (k = 20 items) showed improved RMSEA and SRMR approaching acceptable thresholds.

Table 6 Confirmatory Factor Analysis: Model Fit Indices (WLSMV Estimator).

Model	n	χ^2	df	CFI	TLI	RMSEA	90% CI	SRMR
TRI 2.0 (4 factors)	81	89.90	98	1.000	1.002	.000	[.000, .047]	.074
TAM-IA (6 factors)	77	225.30	174	.998	.997	.062	[.035, .084]	.088

Note. WLSMV = Weighted Least Squares Mean and Variance Adjusted estimator, appropriate for ordinal Likert data with multivariate non-normality (Flora & Curran, 2004). Chi-square p-values are not interpretable under WLSMV distributional assumptions and are therefore omitted. Fit criteria: Hu & Bentler (1999). CFI/TLI ≥ .90 = acceptable, ≥ .95 = good; RMSEA ≤ .08 = acceptable, ≤ .06 = good; SRMR ≤ .08 = acceptable. TRI 2.0 shows excellent fit on all indices. TAM-IA meets CFI/TLI criteria; RMSEA and SRMR are

marginal, attributable in part to CF2 cross-dimensional contamination.

3.6 Standardized Factor Loadings

Table 7 presents standardized CFA factor loadings for TRI 2.0. All loadings were statistically significant ($p < .001$) and ranged from .712 (OPT4) to .927 (OPT3), substantially exceeding the minimum criterion of .50 (Hair et al., 2019). The lowest loading within TRI 2.0 (OPT4 = .712) remained well above the minimum threshold, and its α-if-deleted (.870) was the only case where reliability would marginally increase with item removal — a finding noted but not considered sufficient to justify item exclusion at this pilot stage.

Table 8 presents standardized CFA factor loadings for TAM-IA. All loadings were significant ($p < .001$) and ranged from .670 (CS3) to .977 (IU3). The support conditions subscale showed the weakest loadings (.670–.756), consistent with its reliability results. All remaining subscale items showed loadings ≥ .794, confirming strong reflective measurement of their respective latent constructs.

Table 7 Standardized CFA Factor Loadings: TRI 2.0 (n = 81, WLSMV).

Factor	Item	λ	SE	z	p
Optimism (OPT)	OPT1	.884	.042	21.06	< .001
	OPT2	.809	.043	18.80	< .001
	OPT3	.927	.038	24.28	< .001
	OPT4	.712	.047	15.18	< .001
Innovativeness (INN)	INN1	.846	.050	16.90	< .001
	INN2	.842	.039	21.48	< .001
	INN3	.806	.050	16.26	< .001
	INN4	.876	.037	23.53	< .001
Discomfort (INC)	INC1	.856	.036	23.98	< .001
	INC2	.911	.023	39.26	< .001
	INC3	.904	.030	30.40	< .001
	INC4	.809	.048	16.69	< .001
Insecurity (INS)	INS1	.852	.042	20.45	< .001
	INS2	.784	.044	17.67	< .001
	INS3	.891	.029	30.94	< .001
	INS4	.868	.036	23.96	< .001

Note. λ = standardized factor loading. All loadings significant at p < .001. Minimum criterion: λ ≥ .50 (Hair et al., 2019). All loadings exceed this criterion.

Table 8 Standardized CFA Factor Loadings: TAM-IA (n = 77, WLSMV).

Factor	Item	λ	SE	z	p
Performance Expect. (ED)	ED1	.897	.033	27.56	< .001
	ED2	.972	.015	63.40	< .001
	ED3	.914	.028	32.90	< .001
	ED4	.841	.044	19.30	< .001
Effort Expectancy (EE)	EE1	.928	.029	31.71	< .001
	EE2	.851	.049	17.46	< .001

	EE3	.861	.048	17.90	< .001
	EE4	.794	.047	16.99	< .001
Support Conditions (CS)	CS1	.720	.066	10.84	< .001
	CS2	.756	.072	10.46	< .001
	CS3	.670	.081	8.28	< .001
Trust/Security (CF)	CF1	.833	.042	20.03	< .001
	CF3	.880	.038	23.04	< .001
	CF4	.900	.034	26.50	< .001
AI Disposition (DP)	DP1	.917	.028	32.45	< .001
	DP2	.946	.020	48.08	< .001
	DP3	.956	.019	49.96	< .001
Use Intention (IU)	IU1	.970	.014	70.21	< .001
	IU2	.945	.016	57.41	< .001
	IU3	.977	.013	78.15	< .001

***Note.* λ = standardized factor loading. CF2 excluded from final model (see text). All remaining loadings significant at $p < .001$. CF item CF2 showed extreme modification indices (MI = 35.47–51.48 across factors), confirming cross-dimensional contamination and justifying exclusion.**

3.7 Convergent Validity

Table 9 presents AVE and CR estimates. All TRI 2.0 subscales demonstrated satisfactory convergent validity: AVE ranged from .700 (OPT) to .759 (INC), substantially exceeding the criterion of .50 (Fornell & Larcker, 1981); CR ranged from .903 (OPT) to .926 (INC), well above .70. These results confirm that each TRI 2.0 subscale accounts for more variance in its items than measurement error does.

For TAM-IA, convergent validity was satisfactory across all subscales except support conditions. AVE ranged from .513 (CS) to .929 (IU). CS marginally met the AVE criterion (AVE = .513 ≥ .50), though its low reliability (α = .623) and heterogeneous item loadings (.670–.756) signal that this subscale requires content revision before deployment in structural models. All remaining TAM-IA subscales showed excellent convergent validity (AVE = .739–.929; CR = .919–.975).

Table 9 Convergent Validity: AVE and Composite Reliability.

Instrument	Factor	k	AVE	CR	AVE ≥ .50	CR ≥ .70
TRI 2.0	OPT	4	.700	.903	✓	✓
	INN	4	.710	.907	✓	✓
	INC	4	.759	.926	✓	✓
	INS	4	.722	.912	✓	✓
TAM-IA	ED	4	.823	.949	✓	✓
	EE	4	.739	.919	✓	✓
	CS	3	.513	.759	✓*	✓
	CF	3	.745	.921	✓	✓
	DP	3	.883	.958	✓	✓
	IU	3	.929	.975	✓	✓

***Note.* k = number of items retained in CFA model (CF2 excluded from CF subscale). AVE = Average Variance Extracted = $\Sigma\lambda^2/k$; CR = Composite Reliability = $(\Sigma\lambda)^2/[(\Sigma\lambda)^2 + \Sigma(1 - \lambda^2)]$ (Fornell & Larcker, 1981). *CS meets AVE criterion marginally (AVE = .513); its low reliability (α = .623; ω = .691) and heterogeneous item content indicate revision required prior to definitive validation.**

4. DISCUSSION

4.1 Psychometric Adequacy of TRI 2.0 in the

Ecuadorian Context

The TRI 2.0 demonstrated outstanding psychometric properties in the Ecuadorian university faculty sample. Excellent EFA fit (RMSEA = .034; TLI = .981), perfect CFA fit (CFI = 1.000; RMSEA = .000), and convergent validity exceeding criteria across all four subscales (AVE = .700–.759; CR = .903–.926) collectively confirm that the four-factor structure proposed by Parasuraman and Colby (2015) replicates robustly in this population. These results align with previous TRI 2.0 validations in Latin American service and technology contexts, which have generally found adequate factorial validity while noting cultural nuances in the inhibitor dimensions (Colby & Parasuraman, 2001).

The residual correlation between INS2 and INS4 (MI = 20.11) warrants attention in the definitive validation. Both items address concerns specifically about data privacy and security — a content overlap particularly salient in the AI context, where faculty concerns about data use by AI platforms represent a distinct worry beyond general technology insecurity. Rather than treating this residual as a model misspecification, we interpret it as theoretically meaningful: privacy and security concerns about AI may constitute a specific sub-dimension of insecurity that a revised INS scale could capture with a dedicated item. This interpretation is consistent with findings documenting distinct patterns of AI-specific insecurity among educators (Long & Magerko, 2020).

The motivator subscales (OPT, INN) showed ceiling-proximate mean scores (M = 4.43–5.29 on a 1–6 scale), indicating that this particular sample of online faculty is characterized by generally positive technology predisposition. This finding is substantively plausible — faculty who have self-selected into an online university environment are likely to represent the more technologically disposed segment of the broader faculty population — and has direct implications for sample representativeness in the definitive validation study. Ensuring inclusion of traditional on-site faculty would provide greater variance on motivator subscales and more rigorous tests of their predictive validity.

4.2. The CF2 Anomaly: A Methodological Lesson for AI-Specific TAM Adaptation

The most consequential finding for instrument revision is the identification of CF2 as a source of pervasive cross-dimensional contamination (MI = 35.47–51.48 across all other TAM-IA factors). Content analysis reveals the root cause: CF2 ("I feel safe sharing my personal information with AI platforms when the institution guarantees security") combines behavioral intention (sharing information), institutional trust (guarantee of security), and conditional willingness — a triple-element construction that produces a categorically different response process from the remaining CF items, which measure stable distrust or skepticism about AI reliability without conditional framing. The removal of CF2 resolves the cross-dimensional contamination and yields a three-item CF subscale (CF1, CF3, CF4) with AVE = .745 and CR = .921, meeting all convergent validity criteria.

This case illustrates a general principle for TAM adaptation to AI: items measuring trust must consistently operationalize the same psychological construct — stable perceived trustworthiness of the technology — rather than mixing unconditional appraisals with conditionally-framed behavioral intentions. Future iterations of the TAM-IA should replace CF2 with an item measuring unconditional perceived security of AI data handling, such as: "I believe that AI educational tools handle my information and my students' information responsibly."

4.3 Support Conditions: A Substantive Interpretive Finding

The subthreshold reliability of the CS subscale (α = .623; ω = .691) is not simply a psychometric problem requiring item revision — it is a substantive finding with theoretical implications. The three CS items span two conceptually distinct constructs: (a) institutional infrastructure (availability of technical resources, equipment, training — captured by CS1) and (b) interpersonal encouragement (support from colleagues and supervisors — captured by CS2, CS3). In UTAUT3 terminology, these correspond to facilitating conditions (organizational resources) and social influence (subjective norm) — two originally distinct UTAUT constructs that were collapsed in this instrument's design. Their empirical divergence in this sample reflects the theoretical distinction Venkatesh et al. (2003) originally made.

For Ecuadorian higher education faculty specifically, this finding suggests that institutional infrastructure support and collegial social support operate as distinct mechanisms in the AI adoption process. This has practical implications: interventions designed to improve AI adoption rates should separately target infrastructure provision and peer community building, as these may have differential effects on faculty acceptance trajectories.

4.4 Implications for Structural Modeling

The joint validation of TRI 2.0 and TAM-IA establishes the psychometric foundation for the primary research objective: testing a structural model in which technology predisposition (TRI 2.0 dimensions) predicts AI acceptance dimensions (TAM-IA), which in turn predicts use intention. The excellent measurement quality of three of four TRI 2.0 subscales and five of six TAM-IA subscales (with CS requiring revision and CF2 exclusion) means that the structural model can be estimated with high confidence in measurement validity for the majority of theoretically proposed paths.

Particularly strong theoretical candidates for significant structural paths are: Discomfort (INC) → Use Intention (IU; direct negative relationship); Insecurity (INS) → Trust/Security (CF; the most theoretically direct inhibitor-acceptance link); and Innovativeness (INN) → AI Disposition (DP; both capturing positive orientations toward technology novelty and enjoyment). These hypotheses are grounded in both TRI theory (Parasuraman & Colby, 2015) and the broader predisposition-behavior literature (Taylor & Todd, 1995).

4.5 Limitations

Several limitations constrain the generalizability of these findings. First, the pilot sample (n = 77–81 for instrument-specific analyses) is adequate for exploratory and preliminary confirmatory purposes but falls below recommended thresholds for stable parameter estimation in full structural models (minimum n = 200; Wolf et al., 2013). The definitive validation with the complete sample will enable more precise AVE, CR, and discriminant validity estimation. Second, the sample was drawn from a single private Ecuadorian institution with above-average digital infrastructure — a context that likely inflates motivator scores relative to the broader population of Ecuadorian university faculty. Third, all data were self-reported, introducing potential common method bias, particularly for constructs sharing similar response formats.

5. CONCLUSIONS

This study reports the first joint pilot psychometric validation of TRI 2.0 and an extended TAM for AI (TAM-IA) among university faculty in Ecuador, and among the first in the broader Latin American higher education context. The principal findings are:

TRI 2.0 demonstrates excellent psychometric properties in this population — factorial validity, reliability, and convergent validity all exceeding conventional criteria — and can be recommended for use in structural models examining technology predisposition as a predictor of AI adoption. TAM-IA demonstrates adequate-to-excellent measurement quality across five of six subscales (ED, EE, CF, DP, IU), with two instrument-level revisions indicated prior to definitive validation: exclusion or revision of CF2 (due to cross-dimensional contamination from conditional wording) and conceptual disaggregation of the CS subscale into its infrastructure and social support components (reflecting the theoretically grounded UTAUT distinction between facilitating conditions and social influence).

Together, these two validated instruments provide the measurement infrastructure for a theoretically rigorous examination of how stable technology predispositions shape the cognitive acceptance mechanisms through which Ecuadorian university faculty evaluate and intend to use AI educational tools. This structural question — connecting dispositional antecedents to technology-specific acceptance — represents a meaningful contribution to the literature on faculty technology adoption in the Global South.

Author Contributions: Karla González Vizuete, designed the study, collected data, conducted analyses, and drafted the manuscript. Edison Jair Duque Oliva contributed to theoretical framework development, analysis supervision, and critical manuscript revision.

Acknowledgements: The authors thank the faculty members who participated in this study and the Universidad de Especialidades Espíritu UEES research office for institutional support.

REFERENCES

Abulail, R. N., Alharbi, A., Alkhalaf, S., Alotaibi, F., & Alenezi, M. (2025). Exploring the factors influencing AI adoption intentions in higher education: An integrated model of DOI, TOE, and TAM. Computers, 14(6), 230. https://doi.org/10.3390/computers14060230

Bernaards, C. A., & Jennrich, R. I. (2005). Gradient projection algorithms and software for arbitrary rotation criteria in factor analysis. Educational and Psychological Measurement, 65(5), 676–696. https://doi.org/10.1177/0013164404272507

Colby, C. L., & Parasuraman, A. (2001). Techno-ready marketing: How and why customers adopt technology. Simon and Schuster.

Curran, P. J., West, S. G., & Finch, J. F. (1996). The robustness of test statistics to nonnormality and specification error in confirmatory factor analysis. Psychological Methods, 1(1), 16–29. https://doi.org/10.1037/1082-989X.1.1.16

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

DeVellis, R. F. (2017). Scale development: Theory and applications (4th ed.). SAGE Publications.

Flora, D. B., & Curran, P. J. (2004). An empirical evaluation of alternative methods of estimation for confirmatory factor analysis with ordinal data. Psychological Methods, 9(4), 466–491. https://doi.org/10.1037/1082-989X.9.4.466

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

García-Peñalvo, F. J. (2023). The perception of artificial intelligence in educational contexts after the introduction of ChatGPT: Disruption or panic? Education in the Knowledge Society, 24, e31279. https://doi.org/10.14201/eks.31279

González Vizuete, K. F. (2025). Incidencia de la predisposición tecnológica en la aceptación de la inteligencia artificial en docentes de educación superior [Doctoral dissertation in progress]. Universidad de Especialidades Espíritu Santo.

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

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

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: A Multidisciplinary Journal, 6(1), 1–55. https://doi.org/10.1080/10705519909540118

Jorgensen, T. D., Pornprasertmanit, S., Schoemann, A. M., & Rosseel, Y. (2022). semTools: Useful tools for structural equation modeling (R package version 0.5-6). https://CRAN.R-project.org/package=semTools

Kaiser, H. F. (1974). An index of factorial simplicity. Psychometrika, 39(1), 31–36. https://doi.org/10.1007/BF02291575

Long, D., & Magerko, B. (2020). What is AI literacy? Competencies and design considerations. In Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems (Article 596). Association for Computing Machinery. https://doi.org/10.1145/3313831.3376727

McNeish, D. (2018). Thanks coefficient alpha, we'll take it from here. Psychological Methods, 23(3), 412–433. https://doi.org/10.1037/met0000144

Montero, I., & León, O. G. (2007). A guide for naming research studies in psychology. International Journal of Clinical and Health Psychology, 7(3), 847–862.

Network Readiness Index. (2024). Network readiness index 2024. Portulans Institute. https://networkreadinessindex.org/country/ecuador/

Parasuraman, A. (2000). Technology Readiness Index (TRI): A multiple-item scale to measure readiness to embrace new technologies. Journal of Service Research, 2(4), 307–320. https://doi.org/10.1177/109467050024001

Parasuraman, A., & Colby, C. L. (2015). An updated and streamlined technology readiness index: TRI 2.0. Journal of Service Research, 18(1), 59–74. https://doi.org/10.1177/1094670514539730

Revelle, W. (2023). psych: Procedures for psychological, psychometric, and personality research (R package version 2.3.6). Northwestern University. https://CRAN.R-project.org/package=psych

Rosseel, Y. (2012). lavaan: An R package for structural equation modeling. Journal of Statistical Software, 48(2), 1–36. https://doi.org/10.18637/jss.v048.i02

Salinas, G., & Andrade-Vargas, L. (2024). Los desafíos de la inteligencia artificial en la educación en un mundo tecnologizado. European Public & Social Innovation Review, 9, 1–15. https://doi.org/10.31637/epsir-2024-905

Sandoval-Reyes, J., Idrovo-Carlier, S., & Duque-Oliva, E. J. (2021). Remote work, work stress, and work-life during pandemic times: A Latin American situation. International Journal of Environmental Research and Public Health, 18(13), 7069. https://doi.org/10.3390/ijerph18137069

Taylor, S., & Todd, P. A. (1995). Understanding information technology usage: A test of competing models. Information Systems Research, 6(2), 144–176. https://doi.org/10.1287/isre.6.2.144

Tondeur, J., Van Braak, J., Ertmer, P. A., & Ottenbreit-Leftwich, A. (2017). Understanding the relationship between teachers' pedagogical beliefs and technology use in education: A systematic review of qualitative evidence. Educational Technology Research and Development, 65(3), 555–575. https://doi.org/10.1007/s11423-016-9481-2

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. (2012). 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

Wolf, E. J., Harrington, K. M., Clark, S. L., & Miller, M. W. (2013). Sample size requirements for structural equation models: An evaluation of power, bias, and solution propriety. Educational and Psychological Measurement, 73(6), 913–934. https://doi.org/10.1177/0013164413495237

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(1), 39. https://doi.org/10.1186/s41239-019-0171-0