

Article

Trust, Emotion, and Skepticism in AI-Enabled Academic Marketing: Psychometric Validation and Cross-Validated Machine Learning Evidence from Higher Education

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Abstract

Higher-education institutions increasingly use AI-enabled chatbots, personalised communication, recommendation systems, and predictive information services in academic marketing. Adoption of these systems depends not only on technical availability, but also on institutional trust, emotional engagement, and skepticism regarding the reliability, transparency, and autonomy implications of AI. This study examines the Trust-Tech Nexus framework using stakeholder survey data collected at MIT Art, Design and Technology University, Pune, India ($N = 300$). The analysis combines psychometric validation, WLSMV confirmatory factor analysis for ordered indicators, and cross-validated predictive modelling. Four three-item constructs were measured with five-point Likert indicators, as follows: AI Adoption, Institutional Trust, Emotional Engagement, and AI Skepticism. Reliability and convergent validity were acceptable, and the WLSMV CFA showed strong practical fit ($CFI = 0.991$, $TLI = 0.988$, $RMSEA = 0.040$, $SRMR = 0.039$). Discriminant validity was supported by HTMT and Fornell–Larcker evidence, while Harman’s single-factor result was treated only as an initial diagnostic. Construct-only ridge regression produced positive out-of-sample predictive evidence ($CV\ R\text{-squared} = 0.352$; $RMSE = 0.642$; $MAE = 0.501$). Exploratory classification results were moderate and are interpreted only as supplementary segmentation evidence because the binary targets were derived from the AI Adoption composite. The study supports a validated four-construct measurement structure and moderate predictive association in one institutional context, while avoiding causal claims.

Keywords: artificial intelligence; academic marketing; higher education; institutional trust; emotional engagement; AI skepticism; CFA; WLSMV; machine learning; AI adoption



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1. Introduction

AI-enabled information systems are now part of how universities communicate with prospective students, current students, alumni, staff, and external stakeholders. Institutional interactions may be made more responsive through the use of chatbots, personalised information services, recommendation engines, predictive engagement systems, and AI-assisted communication tools. However, the extent to which these technologies are adopted by stakeholders is a function of those stakeholders’ interpretation of institutional credibility, emotional relevance, and perceived risk of algorithmic mediation. Thus, the adoption of AI in higher education is a social-informatics inquiry rather than a technical inquiry; the same technology may be accepted, resisted, or used cautiously based on trust, emotion, transparency, and perceived autonomy.

The Technology Acceptance Model explains adoption through perceived usefulness and ease of use [1–3], while relationship-marketing and organizational-trust research helps explain why stakeholders are more willing to use institutionally mediated services when they perceive the provider as credible and trustworthy [4–7]. In AI-enabled academic marketing, these perspectives matter because algorithmic systems may be opaque, probabilistic, and personally consequential. Recent reviews of AI in higher education emphasize not only support and personalisation, but also recurring concerns about transparency, trustworthiness, reliability, ethics, and responsible deployment [8–24]. Recent evidence also continues to connect AI acceptance in education with TAM/SEM traditions and trust-oriented adoption mechanisms [14,25,26].

This article develops and tests a Trust-Tech Nexus perspective in which AI Adoption is examined in relation to Institutional Trust, Emotional Engagement, and AI Skepticism. The contribution is not the invention of entirely new constructs, but their context-specific integration for AI-enabled academic marketing in higher education, the transparent 12-item operationalization, and the combination of ordered-indicator CFA with out-of-sample predictive validation. The study addresses three research questions, as follows: RQ1, does the proposed four-construct measurement structure meet accepted reliability and validity standards? RQ2, how are Institutional Trust, Emotional Engagement, and AI Skepticism associated with AI Adoption? RQ3, do these constructs provide meaningful cross-validated predictive evidence for AI Adoption? The machine learning component is used as a predictive and exploratory supplement, not as causal evidence [27–32]. Practically, the findings are intended to inform how universities design and govern AI-enabled academic communication including AI chatbots, personalised communication, recommendation systems, and predictive information services so that adoption is reinforced by institutional trust and emotional engagement while skepticism is addressed through transparency rather than treated as mere resistance. Within Informatics, the study is positioned at the intersection of AI-enabled information systems, institutional trust, human– technology interaction, and the social conditions that shape stakeholder adoption in higher education.

Figure 1 presents the Trust-Tech Nexus conceptual framework used to organize the theoretical relationships among Institutional Trust, Emotional Engagement, AI Skepticism, and AI Adoption.

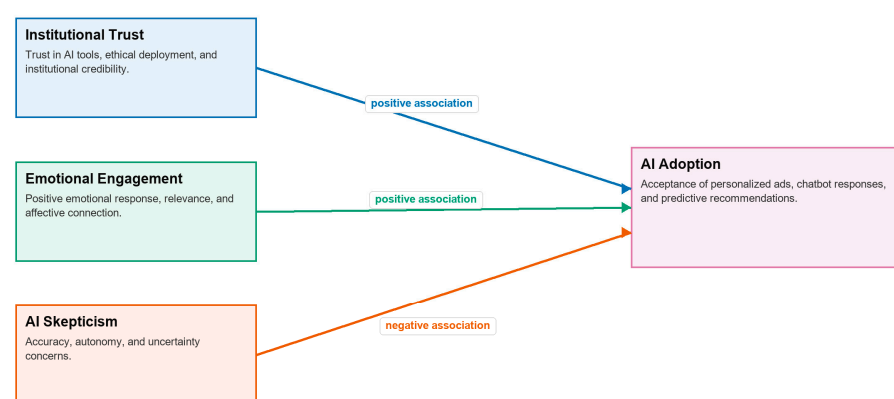


Figure 1. Trust-Tech Nexus conceptual framework for AI-enabled academic marketing in higher education.

The framework positions AI Adoption as a stakeholder response shaped by Institutional Trust, Emotional Engagement, and AI Skepticism within an institutionally mediated academic communication and decision-support environment. Institutional Trust and Emotional Engagement are specified as positive correlates because greater perceived institutional credibility and stronger affective engagement are expected to increase stakeholder

willingness to use AI-enabled academic communication tools. By contrast, AI Skepticism is specified as a negative correlate because concerns about opacity, inaccuracy, and reduced autonomy are expected to reduce willingness to rely on AI-supported institutional interactions. The model is conceptually bounded to the higher-education context and is not proposed as a universal framework for all forms of AI adoption.

2. Theoretical Background

2.1. AI Adoption and Institutional Trust

The Technology Acceptance Model and its extensions remain central to explaining technology acceptance [1–3]. In AI-enabled academic marketing, however, the perceived usefulness of personalised advertisements, chatbots, and predictive recommendations cannot be separated from the institutional setting in which these services are delivered. Stakeholders evaluate not only whether the tool is useful, but also whether the institution deploying it is credible, responsible, and transparent. Research across digital service settings shows that trust reduces uncertainty and can increase willingness to use institutionally mediated systems [4–7].

2.2. Emotion and AI Skepticism

Emotion also shapes judgments and decision-making, especially when information is uncertain or personally consequential [33,34]. In academic marketing, emotionally engaging AI communication may make institutional messages feel more relevant, responsive, and personally meaningful. At the same time, technology-readiness and resistance perspectives explain why users may resist tools that appear intrusive, inaccurate, or autonomy reducing [35,36]. In the present study, AI Skepticism is used as a practical construct that captures accuracy concerns, autonomy concerns, and uncertainty concerns. The framework therefore expects Institutional Trust and Emotional Engagement to be positively associated with AI Adoption, whereas AI Skepticism is expected to be negatively associated with adoption.

2.3. Positioning Within AI-in-Education Research

Recent AI-in-education research has documented both the opportunities and the governance challenges associated with AI-enabled communication, recommendation, and support systems [8–24,37,38]. What remains underdeveloped is a bounded account of AI adoption in academic marketing, where institutional reputation, stakeholder aspirations, AI-assisted services, and decision confidence converge. In this paper, academic marketing is defined as the AI-supported communication and service layer through which a higher-education institution informs, guides, and engages prospective and current stakeholders about academic opportunities, choices, and institutional offerings. Concretely, academic marketing in this sense covers AI-powered programme recommendations, chatbot-based admissions guidance, personalised course information, and predictive student communication. It is therefore distinct from broader learning analytics, general student-support services, and routine administrative or institutional communication, which respectively centre on instructional performance, student welfare, and operational messaging rather than on the decision-oriented, institutionally mediated engagement through which stakeholders evaluate academic opportunities and offerings.

The distinctiveness of the Trust-Tech Nexus framework lies in three linked contributions. First, it brings together institutional trust, emotional engagement, and skepticism within a single higher-education academic-marketing context rather than treating them as isolated explanatory variables. Second, it operationalizes these constructs through a transparent 12-item instrument that is explicitly mapped to both measurement and predictive analyses. Third, it separates measurement validation, predictive validation, and causal

interpretation, thereby positioning the machine learning component as an out-of-sample robustness exercise rather than as a claim of algorithmic novelty.

The theoretical rationale for integrating these constructs is that AI-enabled academic marketing is not experienced by stakeholders as a purely functional information system. Rather, it is encountered as an institutionally mediated decision-support environment in which perceived credibility, emotional resonance, and concerns about opacity, inaccuracy, or reduced autonomy jointly shape willingness to engage with AI-supported communication. The Trust-Tech Nexus framework therefore treats Institutional Trust, Emotional Engagement, and AI Skepticism as complementary dimensions of stakeholder evaluation rather than as isolated predictors. Accordingly, the framework is conceptually bounded, as follows: it is not proposed as a universal model of all AI adoption, but as a higher-education-specific account of how stakeholders evaluate AI-mediated academic communication and service interactions.

3. Materials and Methods

3.1. Research Design and Dataset

This study used a cross-sectional survey design to examine stakeholder responses to AI-enabled academic communication and service interactions in a higher-education setting. Data were collected between 1 January 2024 and 31 December 2024 at MIT Art, Design and Technology University, Pune, India. The dataset consists of respondent-level survey data and contains 300 valid completed responses with no missing values for the 12 Likert-scale indicators used in the core analysis. Each indicator was measured on a five-point scale ranging from 1 = Strongly Disagree to 5 = Strongly Agree. The design supports psychometric validation and predictive modelling, but it does not support causal inference.

Purposive sampling was used because the target population consisted of stakeholders with awareness of, or exposure to, AI-enabled academic communication tools and services, including chatbots, personalised advertisements, recommendation systems, and AI-supported institutional information services. Inclusion was therefore based on stakeholder relevance to the institution's academic communication environment rather than random selection from a broader population. Because the survey link was distributed through institutional communication channels and the number of unique invited participants was not archived in a verifiable way, a precise response rate could not be calculated.

The final dataset combined UG students, PG students, faculty, administrative staff, and other institutionally relevant respondents into one pooled stakeholder population. This approach was adopted because the principal aim of the study was institution-level construct validation and predictive testing within a shared AI-supported academic communication environment, rather than subgroup comparison. Although respondents may not all have interacted with an identical interface, they were recruited from the same institutional AI-supported communication environment. The focus of the analysis was therefore on whether the proposed Trust-Tech Nexus constructs and their relationships were empirically defensible across the institutional communication ecosystem as a whole. At the same time, these stakeholder groups may differ in their experiences of, expectations of, and reliance on AI-enabled academic marketing. Accordingly, the pooled analysis should not be interpreted as implying subgroup equivalence, and subgroup-specific analyses remain an important direction for future research.

Initial data screening confirmed 300 usable cases, zero duplicated respondent identifiers, complete responses for all Q1–Q12 items, and valid five-point Likert ranges for every measurement indicator. Demographic variables were retained for sample description and supplementary control models, whereas the primary predictive models used only the construct-level predictors in order to preserve interpretive clarity and avoid unnecessary

dimensionality. Sample adequacy was evaluated with reference to both the measurement model and the predictive analysis. For WLSMV CFA, $N = 300$ is adequate for a four-factor model with 12 ordered indicators. The predictive models were intentionally low-dimensional and evaluated using deterministic 10-fold cross-validation to reduce overfitting and provide an out-of-sample assessment of predictive utility. Because the study was designed as an exploratory institution-level validation exercise, the pooled analysis is used to characterize the shared higher-education communication environment rather than to imply that every subgroup experienced AI-enabled services in the same way. The respondent profile and study context utilized in the empirical analyses are presented in Table 1.

Table 1. Respondent profile summary ($N = 300$).

Variable	Most Frequent Categories
Role	UG Student: 114; PG Student: 55; Faculty: 52; Administrative Staff: 32; Other/Not specified: 47
Gender	Male: 168; Female: 127; Prefer not to say: 5
AI experience	Moderate: 119; Extensive: 91; Limited: 64; Other/Not specified: 26
Institution	MIT Art, Design and Technology University, Pune, India

Table 1 shows that the study reflects a single-institution higher-education stakeholder sample drawn from MIT Art, Design and Technology University, Pune, India. The respondent pool includes students, faculty, administrative staff, and other institutionally relevant respondents, and should therefore be interpreted as institution-level exploratory evidence rather than as a representative sample of a broader population.

Table 2 reports descriptive statistics for the principal internal stakeholder groups, as follows: students, faculty, and administrative staff. Groupwise descriptive comparisons did not indicate differences of a magnitude that would invalidate pooled institution-level exploratory analysis; therefore, the variables were modelled for the sample as a whole. One-way ANOVA results likewise did not indicate statistically notable between-group mean differences for AI Adoption ($F = 0.041$, $p = 0.959$), Institutional Trust ($F = 0.678$, $p = 0.509$), Emotional Engagement ($F = 0.038$, $p = 0.963$), or AI Skepticism ($F = 0.179$, $p = 0.836$).

Table 2. Descriptive statistics for construct composites by stakeholder group.

Construct	Students Mean	Students SD	Faculty Mean	Faculty SD	Administrative Staff Mean	Administrative Staff SD
AI Adoption	3.071	0.799	3.045	0.756	3.094	0.710
Institutional Trust	3.205	0.775	3.167	0.807	3.031	0.818
Emotional Engagement	2.970	0.791	3.000	0.803	2.958	0.722
AI Skepticism	2.738	0.829	2.776	0.713	2.667	0.859

3.2. Measures and Construct Scoring

The 12-item instrument was developed as a theory-driven, context-specific measure for AI-enabled academic marketing in higher education. Item wording was informed by prior literature on AI adoption, institutional trust, affective judgment, and technology resistance, and then adapted to reflect the communication and decision-support context of higher-education institutions. The questionnaire was reviewed during instrument preparation for wording clarity, contextual fit, and interpretive consistency before final administration. Negatively framed skepticism items were handled consistently during composite-score construction so that higher values reflected higher AI Skepticism throughout the analysis.

At the same time, the study does not assume that all item-to-construct mappings are conceptually perfect. Some AI Skepticism items may also reflect autonomy-related concern or decision anxiety, while the Institutional Trust construct includes both trust in institutional credibility and trust in AI-supported institutional deployment. Accordingly, the instrument is interpreted as an internally coherent applied measure for the present study rather than as a definitive final taxonomy of AI-related stakeholder attitudes. Because the instrument was validated in a single institutional context and uses only three indicators per construct, it should be regarded as a context-specific applied measure rather than a final general-purpose scale for AI adoption in higher education; broader generalization would require replication and further psychometric development across institutions. The questionnaire measured four constructs using three indicators each. AI Adoption was measured through items on personalised advertisements, chatbot responses, and predictive recommendations. Institutional Trust combined trust in AI tools, trust in ethical institutional deployment, and trust in institutional credibility. Emotional Engagement captured positive emotional response and affective connection. AI Skepticism captured concerns about accuracy, reduced autonomy, and uncertainty. Composite scores were computed as the arithmetic mean of the three appropriate items for each construct.

Table 3 presents the exact wording of all 12 Trust-Tech Nexus indicators so that the measurement instrument remains transparent and reproducible.

Table 3. Trust-Tech Nexus measurement instrument and item wording.

Construct	Code	Variable	Exact Item Wording
AI Adoption	Q1_PA	Personalised Ads	AI-personalised advertisements help me make better academic programme decisions.
AI Adoption	Q2_CR	Chatbot Responses	AI chatbot responses are useful in assisting my academic marketing interactions.
AI Adoption	Q3_PR	Predictive Recommendations	AI predictive recommendations meaningfully improve my academic decision-making confidence.
Institutional Trust	Q4_TAI	Trust in AI Tools	I trust the AI tools deployed by MIT ADT University for academic marketing purposes.
Institutional Trust	Q5_TU	Trust in University	I trust MIT ADT University to deploy AI technologies in an ethical and responsible manner.
Institutional Trust	Q6_PU	Perception of University	MIT ADT University has a positive and credible reputation in its approach to AI technologies.
Emotional Engagement	Q7_EE	Emotional Engagement	AI-driven marketing interactions at MIT ADT engage me emotionally in a positive way.
Emotional Engagement	Q8_ER	Emotional Response	I experience a positive emotional response when engaging with AI-mediated academic content from MIT ADT.
Emotional Engagement	Q9_ACA	Affective Connection to AI	I feel a meaningful affective connection when interacting with AI-powered marketing tools at MIT ADT.
AI Skepticism	Q10_SAI	Skepticism Toward AI	I am skeptical about the accuracy and reliability of AI claims in academic marketing at MIT ADT.
AI Skepticism	Q11_DMC	Decision-Making Confidence	AI systems reduce my confidence in making independent and informed academic decisions.
AI Skepticism	Q12_AUC	AI Uncertainty Concern	I have significant concerns about the uncertainty and unpredictability of AI in higher education at MIT ADT.

(All items used a five-point Likert scale from 1 = Strongly Disagree to 5 = Strongly Agree).

Table 3 defines the latent constructs transparently before CFA and predictive results are interpreted, improving reproducibility and reducing ambiguity about what each construct measures.

Table 4 provides an overview of how each construct maps to its observed indicators and how those constructs were used in the predictive models.

Table 4. Construct-feature alignment.

Construct	Observed Items	Role in Models
AI Adoption	Q1_PA, Q2_CR, Q3_PR	Primary regression target; source of exploratory binary targets
Institutional Trust	Q4_TAI, Q5_TU, Q6_PU	Predictor
Emotional Engagement	Q7_EE, Q8_ER, Q9_ACA	Predictor
AI Skepticism	Q10_SAI, Q11_DMC, Q12_AUC	Predictor

Table 4 also clarifies the modelling logic, as follows: the target construct is separated from the predictor constructs, which reduces ambiguity about feature construction and leakage risk.

Figure 2 summarizes the end-to-end analysis pipeline from raw Excel data through psychometric validation, CFA, and cross-validated predictive evaluation.

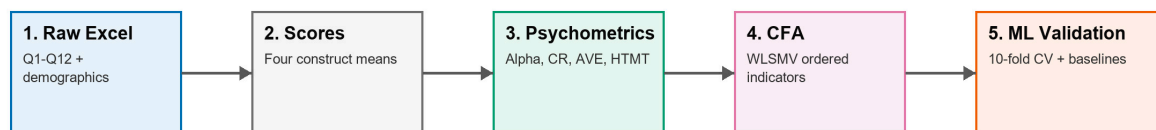


Figure 2. End-to-end analysis pipeline from raw Excel data to cross-validated machine learning models.

Figure 2 shows prediction as the final stage of a broader validation workflow that begins with data screening, construct scoring, reliability checks, and measurement validation.

The HTMT matrix, the Fornell–Larcker matrix, and the lavaan output were examined directly during the measurement validation stage.

3.3. Psychometric and CFA Procedure

Reliability was assessed using Cronbach’s alpha. Convergent validity was assessed using composite reliability, average variance extracted, and standardized factor loadings. Discriminant validity was assessed with Fornell–Larcker comparisons and HTMT ratios [39,40]. Common method bias was screened with Harman’s single-factor diagnostic [41]. Because the indicators are ordered Likert items, CFA was estimated in lavaan using WLSMV and ordered indicators [42,43]. WLSMV was preferred because five-point Likert responses are ordered as categorical rather than continuous variables; estimators that assume continuous, normally distributed indicators can distort factor loadings and fit statistics for such data, whereas WLSMV draws on polychoric correlations and is robust to non-normality, making it appropriate for ordinal-indicator CFA. Model fit was evaluated using CFI, TLI, RMSEA, and SRMR, following established SEM guidance [44].

Statistical analyses were conducted using R version 4.4.2 with the lavaan package version 0.6-19 for WLSMV confirmatory factor analysis. Machine-learning analyses were conducted using Python version 3.12.4 with scikit-learn version 1.5.1. Microsoft Excel 2021 was used for data organization. No chemicals, reagents, laboratory devices, instruments, commercial cell lines, or commercial biological samples/materials were used in this study.

Because the study relied on self-reported questionnaire data, procedural steps were taken to reduce avoidable ambiguity in measurement. The instrument used consistent response anchors, clearly structured item wording, and construct-level organization, and it was reviewed during instrument preparation for wording clarity, contextual fit, and interpretive consistency before final administration. Participants were informed that responses would be used only for academic research purposes and would be treated confidentially, which was intended to

reduce evaluation apprehension and socially desirable responding. However, the design did not include temporal separation of predictors and outcomes, a marker variable, or a common latent factor sensitivity model. Accordingly, common method variance cannot be ruled out and must be considered when interpreting the observed associations.

3.4. Machine Learning Procedure and Leakage Controls

The machine learning analysis recalculated all composite scores directly from Q1–Q12. The primary regression target was AI Adoption Score, computed as the mean of Q1–Q3. The primary predictors were Institutional Trust, Emotional Engagement, and AI Skepticism. To prevent target leakage, Q1–Q3 were never included as predictors when predicting AI Adoption. Model evaluation used deterministic 10-fold cross-validation. Regression performance was assessed using R-squared, RMSE, and MAE. Baseline performance was calculated using mean prediction for regression (RMSE = 0.797; MAE = 0.633) and majority-class prediction for classification (median target accuracy baseline = 0.617; AI Adoption ≥ 3.5 target baseline = 0.727). Machine learning was used as a complementary out-of-sample validation strategy rather than as a substitute for regression or SEM-based interpretation. Given the small number of construct-level predictors, the purpose of this step was not algorithmic novelty but to assess whether the validated constructs retained predictive utility under leakage-controlled cross-validation. The predictive component was therefore designed as a robustness-oriented extension of the psychometric and CFA analysis rather than as a stand-alone machine learning contribution.

4. Results

4.1. Descriptive Statistics

Table 5 reports the descriptive statistics for the four composite construct scores used in the main analysis.

Table 5. Descriptive statistics for construct composites.

Construct	Mean	SD	Min	Max
AI Adoption	3.060	0.799	1.000	5.000
Institutional Trust	3.171	0.787	1.000	5.000
Emotional Engagement	2.979	0.787	1.000	5.000
AI Skepticism	2.743	0.800	1.000	4.667

Table 5 suggests that the constructs have enough empirical variability to allow for their use for association and predictive analysis; however, they are all bounded by the use of a five-point scale. The correlations suggest that AI Adoption had positive correlations with both Institutional Trust and Emotional Engagement but did not have strong correlations with AI Skepticism; this supports the anticipated directional associations and remains consistent with the discriminant validity evidence.

The relatively modest simple association between AI Skepticism and AI Adoption may indicate that skepticism does not always translate into outright rejection in this context. While higher-education stakeholders may have reservations about the potential accuracy, opacity, or autonomy implications of AI in academic communication tools that are enabled by AI, usage of such tools is pragmatically beneficial. Utility and skepticism may go hand-in-hand when these tools are used for accessing information and assisting the decision-making process. Such qualitative patterns of skepticism and utility as AI is used instrumentally will likely be relevant for the adoption of AI in Indian higher education as well; users may be pragmatically evaluating the benefits of AI, while concurrently being concerned about issues related to reliability, transparency, and control.

4.2. Reliability, Validity, and CFA

Table 6 presents the construct-level reliability and convergent-validity evidence.

Table 6. Reliability and convergent-validity summary.

Construct	Alpha	CR	AVE	Min CITC
AI Adoption	0.801	0.883	0.716	0.632
Institutional Trust	0.806	0.886	0.721	0.651
Emotional Engagement	0.800	0.883	0.715	0.615
AI Skepticism	0.781	0.873	0.696	0.609

Table 6 shows that predictive modelling was applied only after the constructs demonstrated acceptable internal reliability and convergent validity. All reliability estimates exceeded the conventional 0.70 threshold. The four-factor WLSMV CFA also showed strong practical model fit. Although the scaled chi-square statistic was significant, practical fit indices formed the main basis of interpretation because chi-square is sensitive to sample size.

Table 7 reports the CFA fit indices, Table 8 reports the full standardized WLSMV factor loadings with standard errors and significance levels, and Table 9 reports the latent factor correlations together with the Fornell–Larcker discriminant-validity summary. The full standardized loading output, the HTMT matrix, the ordinal thresholds for the ordered indicators, and the exact lavaan model specification were examined directly during measurement validation.

Table 7. Confirmatory factor analysis fit and validity diagnostics.

Diagnostic	Observed Value	Recommended Threshold / Interpretation	Conclusion
Scaled chi-square	70.977	Lower values preferred; sensitive to <i>N</i>	Acceptable with strong practical fit
df	48	Model degrees of freedom	Identified model
<i>p</i> -value	0.017	May be significant with <i>N</i> = 300	Interpreted with practical fit indices
CFI	0.991	>0.95	Excellent fit
TLI	0.988	>0.95	Excellent fit
RMSEA	0.040	<0.06	Good fit
SRMR	0.039	<0.08	Good fit

Table 8. Standardized WLSMV CFA loadings for the Trust-Tech Nexus measurement model.

Construct	Item	Standardized Loading	SE	z-Value	<i>p</i> -Value
AI Adoption	Q1_PA	0.835	0.209	7.267	<0.001
AI Adoption	Q2_CR	0.795	0.157	8.353	<0.001
AI Adoption	Q3_PR	0.759	0.129	9.034	<0.001
Institutional Trust	Q4_TAI	0.825	0.196	7.465	<0.001
Institutional Trust	Q5_TU	0.813	0.186	7.523	<0.001
Institutional Trust	Q6_PU	0.772	0.14	8.689	<0.001
Emotional Engagement	Q7_EE	0.821	0.191	7.534	<0.001
Emotional Engagement	Q8_ER	0.787	0.162	7.86	<0.001
Emotional Engagement	Q9_ACA	0.801	0.164	8.143	<0.001
AI Skepticism	Q10_SAI	0.822	0.216	6.691	<0.001
AI Skepticism	Q11_DMC	0.763	0.161	7.361	<0.001
AI Skepticism	Q12_AUC	0.745	0.153	7.313	<0.001

Note: All standardized factor loadings were statistically significant at $p < 0.001$.

Table 9. Latent factor correlations and Fornell–Larcker discriminant-validity summary.

Construct	AI Adoption	Institutional Trust	Emotional Engagement	AI Skepticism
AI Adoption	0.797	0.535	0.663	−0.562
Institutional Trust	0.535	0.804	0.544	−0.500
Emotional Engagement	0.663	0.544	0.803	−0.522
AI Skepticism	−0.562	−0.500	−0.522	0.777

Note: Diagonal values are the square roots of AVE. Discriminant validity is supported when each diagonal value exceeds the corresponding inter-construct correlations. HTMT results were also examined as an additional discriminant-validity diagnostic.

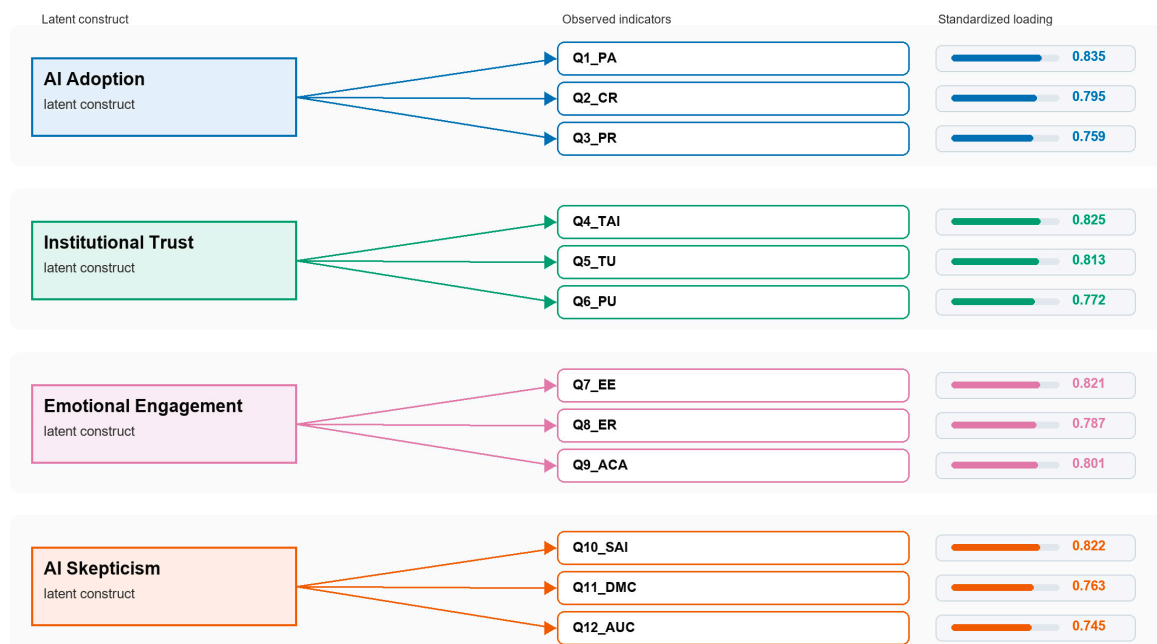
Tables 7–9 together show that the four-factor measurement structure is empirically defensible for ordered Likert indicators and sufficiently documented for independent scrutiny rather than relying only on summary claims.

Table 10 presents the HTMT matrix as an additional discriminant-validity diagnostic. All off-diagonal HTMT values remained below the conservative 0.85 threshold, supporting the distinctiveness of the four construct domains.

Table 10. HTMT discriminant-validity matrix.

Construct	AI Adoption	Institutional Trust	Emotional Engagement	AI Skepticism
AI Adoption	-	0.528	0.662	0.551
Institutional Trust	0.528	-	0.539	0.490
Emotional Engagement	0.662	0.539	-	0.519
AI Skepticism	0.551	0.490	0.519	-

Figure 3 illustrates that each indicator contributes meaningfully to its intended latent construct, strengthening the bridge between item wording and construct-level interpretation.

**Figure 3.** WLSMV CFA measurement model with standardized factor loadings.

4.3. Discriminant Validity and Common Method Bias

Discriminant validity was supported by HTMT values below the conservative 0.85 threshold and by Fornell–Larcker comparisons. Harman’s single-factor diagnostic was

treated only as an initial screening result rather than as a definitive test of common method variance. Although the first unrotated factor did not account for a dominant share of total variance, the predictor constructs and the AI Adoption outcome were collected from the same respondents using the same questionnaire at the same point in time. As a result, common method variance remains a meaningful limitation, and the observed associations may be somewhat inflated by shared method effects even though the measurement and validity diagnostics were otherwise acceptable [41]. Future research could address common method variance more directly through temporal separation of predictor and outcome measurement, the inclusion of objective behavioural usage data, the use of marker variables, and triangulation with multi-source institutional records, rather than relying solely on concurrent self-reports from the same respondents.

4.4. Cross-Validated Machine Learning Results

Cross-validated predictive performance against relevant classification and regression baselines is displayed in Table 11. Predictive evidence for the study is primarily provided by the regression results, as they directly match the construct-level development for the study as well as retain the continuous nature of the AI Adoption results. By contrast, classification results are supplementary because the binary targets were derived from the AI Adoption composite and therefore function only as exploratory segmentation checks rather than as independent theoretical outcomes. In particular, they are recoded from the self-reported AI Adoption composite rather than measured as independent behavioural outcomes such as actual system-usage logs. The machine learning results should therefore be interpreted as moderate out-of-sample predictive evidence rather than as a claim of advanced algorithmic performance.

Table 11. Cross-validated predictive performance.

Analysis Type	Model/Target	Metric	Observed Value	Baseline/Comparator	Interpretation
Regression	Ridge regression	CV R-squared	0.352	0 = mean baseline	Positive out-of-sample signal
Regression	Ridge regression	CV RMSE	0.642	Mean baseline RMSE = 0.797	Better than baseline
Regression	Ridge regression	CV MAE	0.501	Mean baseline MAE = 0.633	Better than baseline
Classification	Median adoption target	Accuracy	0.703	Majority baseline = 0.617	Moderate improvement
Classification	Median adoption target	Accuracy	0.703	Majority baseline = 0.617	Moderate improvement
Classification	Median adoption target	Balanced accuracy	0.664	0.500 random baseline	Moderate discrimination
Classification	Median adoption target	F1	0.776	Positive-class prevalence comparator	Useful segmentation signal
Classification	Median adoption target	ROC-AUC	0.769	0.500 random baseline	Acceptable discrimination
Classification	Median adoption target	PR-AUC	0.833	Positive prevalence = 0.617	Useful segmentation signal

Regression results provide the primary predictive evidence, whereas classification remains supplementary because the binary targets were derived from the AI Adoption composite.

Table 11 indicates that Institutional Trust, Emotional Engagement, and AI Skepticism contain out-of-sample predictive information about AI Adoption, but that this evidence is best interpreted as moderate predictive association in one institutional context rather than as broad validation of AI adoption behaviour.

Permutation-based importance results follow the same directional pattern, with Emotional Engagement contributing the largest increase in prediction error when perturbed, followed by AI Skepticism and Institutional Trust.

Construct-only regression models provided meaningful out-of-sample predictive evidence for AI Adoption. Ridge regression produced cross-validated RMSE = 0.642 and MAE = 0.501 in the verified rerun, improving on the mean-prediction baseline RMSE of 0.797. In

the standardized ridge summary, Emotional Engagement showed the strongest positive predictive contribution ($\beta = 0.288$), Institutional Trust showed a smaller positive contribution ($\beta = 0.146$), and AI Skepticism showed a negative contribution ($\beta = -0.172$). The machine learning component is therefore useful as an out-of-sample robustness check, but its novelty is modest because the model relies on only three validated construct-level predictors. Classification results showed only moderate segmentation performance and are treated as supplementary robustness evidence rather than as a central contribution.

Table 12 summarizes the standardized predictive contribution pattern of the three construct-level predictors. Emotional Engagement showed the strongest positive predictive contribution to AI Adoption, Institutional Trust showed a smaller positive contribution, and AI Skepticism showed a negative contribution. This pattern was also consistent with the permutation-based importance results. These values are interpreted as moderate predictive associations under cross-validation rather than as causal effects.

Table 12. Standardized predictive contributions and interpretation summary.

Predictor	Standardized Ridge Coefficient	Direction	Relative Importance Summary
Emotional Engagement	0.288	Positive	Strongest predictive contribution
Institutional Trust	0.146	Positive	Smaller positive contribution
AI Skepticism	−0.172	Negative	Negative predictive contribution

Note: Coefficients are based on the standardized ridge regression summary from the construct-only predictive model. Values are interpreted as moderate predictive associations under cross-validation rather than as causal effects.

Figure 4 provides a compact visual summary of the cross-validated machine learning performance metrics.



Figure 4. Cross-validated predictive-performance summary.

Classification is supplementary exploratory evidence. Figure 4 shows that predictive performance is most informative when interpreted against explicit baselines and leakage controls rather than as evidence of causal effects.

5. Discussion

The results support the psychometric adequacy of the Trust-Tech Nexus constructs in this dataset. Reliability, convergent validity, WLSMV CFA fit, discriminant validity, and common-method screening all met accepted thresholds. This matters because predictive

modelling should not be applied to poorly defined constructs. Establishing measurement adequacy first strengthens the interpretation of the subsequent predictive results.

Institutional Trust was positively associated with AI Adoption, supporting the view that stakeholders evaluate AI-enabled marketing partly through the credibility and governance of the institution deploying the tools. This interpretation is consistent with recent higher-education evidence showing that trust remains a differentiating factor across students, teachers, and researchers using generative AI tools, and that adoption among students and lecturers is shaped by whether AI is perceived as dependable and institutionally supported [14,45,46]. Emotional Engagement was a strong positive predictor, reinforcing the idea that adoption is shaped by perceived relevance and affective connection as well as by instrumental judgments. Recent work on AI-mediated persuasion and digital marketing likewise suggests that trust transfer, mediated credibility, and emotionally resonant AI communication can strengthen user responsiveness to AI-supported interactions [47,48]. AI Skepticism was negatively associated with adoption, consistent with technology-resistance perspectives [35,36], but the modest simple correlation suggests that caution may coexist with pragmatic use when stakeholders still perceive AI tools as useful for information access and decision support; this interpretation also aligns with recent comparative and dual-perspective higher-education studies [45,46]. The machine learning component serves as a cross-validated robustness check rather than as a replacement for theory-driven modelling. In the present study, the predictive analysis complements the psychometric and CFA results by showing that the validated constructs retain moderate out-of-sample association with AI Adoption. The exploratory classification findings may be useful for segmentation logic, but they remain secondary because both binary targets were derived from the same AI Adoption composite. Because these associations were estimated at the pooled institution level, they characterise the stakeholder population as a whole and should not be read as implying that students, faculty, and administrative staff experience AI-enabled academic marketing in the same way; subgroup-specific analysis therefore remains an important direction for future research.

5.1. Theoretical Contributions

From a theoretical perspective, the study advances the literature by integrating institutional trust, emotional engagement, and skepticism within a bounded AI-supported academic-marketing framework rather than presenting a generic adoption model. From a methodological perspective, it combines ordered-indicator CFA with leakage-controlled cross-validated prediction while clearly separating measurement validity, predictive evidence, and causal interpretation.

5.2. Practical Implications

These findings indicate that AI-supported academic marketing in higher education should be treated as a trust-building and decision-support service rather than as an efficiency tool alone. Transparent communication about the role of AI, clear explanation of how recommendations are generated, user control over AI-enabled interactions, and a clear escalation path from automated support to a human adviser may help reduce skepticism while preserving critical awareness of AI use. This emphasis on trust-building and transparent governance is also consistent with recent research on AI adoption in digital-marketing and consumer-technology settings, where credibility cues, cybersecurity awareness, and trust-transfer mechanisms shape willingness to engage with AI-enabled systems [47–49]. Universities should tell stakeholders when they are interacting with AI-enabled systems, clarify the goals and limits of AI-assisted recommendations, provide fallback options for human interaction, and monitor stakeholder skepticism as a potential indicator of governance concerns rather than treating it simply as resistance.

6. Reproducibility and Analytical Safeguards

Each stage of the analysis followed a conservative validation sequence, as follows: first measurement validity, then construct scoring, and only then predictive modelling. Q1–Q3 were excluded from the predictor set when estimating AI Adoption in order to prevent target leakage. Classification remained exploratory rather than central to the study's theoretical argument. The single-institution cross-sectional design was treated as a boundary on generalisation rather than as an opportunity for causal inference. The findings therefore establish measurement adequacy, associative structure, and cross-validated predictive evidence, but they do not establish temporal order or causal mechanisms.

7. Limitations and Future Research

This study has several limitations. First, it examines data from a single higher-education institution in India, so the findings require validation across multiple institutions, stakeholder populations, and geographic settings. Second, the design is cross-sectional, which prevents conclusions about temporal ordering or causal mechanisms. Third, although groupwise composite differences were limited in the present sample, the pooled design still combines stakeholder groups that may have different experiences of AI-enabled academic marketing; subgroup-specific analyses and formal invariance testing therefore remain important directions for future research. Fourth, the classification targets were derived from the AI Adoption composite and should be regarded as exploratory rather than definitive. Future studies should validate the Trust-Tech Nexus framework using separate samples, longitudinal designs, and objective behavioural measures where possible. In particular, future work should test the framework across multiple universities, compare public and private institutions, incorporate actual AI usage logs alongside self-reported measures, and examine whether institutional trust and AI skepticism operate differently among students, faculty, and administrative staff.

8. Conclusions

The present study examined the Trust-Tech Nexus model of AI Adoption in academic marketing using psychometric validation, WLSMV CFA, and cross-validated predictive modelling. The four-construct measurement structure demonstrated acceptable reliability, convergent validity, discriminant validity, and strong practical CFA fit for the ordered Likert indicators. Within this validated framework, AI Adoption was positively associated with Emotional Engagement and Institutional Trust and negatively associated with AI Skepticism. The results further indicate that these constructs retain moderate out-of-sample association with AI Adoption within one institutional setting. Overall, the study provides a defensible measurement framework for examining AI adoption in academic marketing while keeping interpretation appropriately bounded to associative and predictive evidence rather than broad causal claims. Future research should extend this framework across multiple institutions, stakeholder groups, and longitudinal settings to assess wider generalisability and temporal robustness.

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