

How Perceived University Support Shapes Marketing Students' AI Self-Efficacy: *A Multigroup Dual-Mediation TAM Analysis Across Three Chinese Universities*

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Abstract

The proliferation of artificial intelligence (AI) in marketing has prompted higher education institutions to invest substantially. However, a critical pedagogical question remains: whether and how these institutional investments translate into students' psychological readiness to deploy AI tools effectively. Students' AI self-efficacy constitutes a foundational prerequisite for technology adoption and career adaptability. A lack of such confidence can precipitate technology avoidance behaviors and diminish learning engagement. Drawing on the Technology Acceptance Model (TAM) as a cognitive-mediation framework, this study investigates how perceived university support (PUS) shapes marketing students' AI self-efficacy (AISE) through the dual mediating beliefs of perceived usefulness (PU) and perceived ease of use (PEOU), and whether this mechanism holds across institutionally heterogeneous settings. Using structural equation modeling with a sample of 538 marketing students from three Chinese universities, we find that PUS significantly enhanced both PU and PEOU in all samples, and that both beliefs carried the effect of support to self-efficacy. PU and PEOU mediated the PUS–AISE relationship: the indirect effect via PEOU was consistently stronger than that via PU, and the direct PUS–AISE path remained significant in two of the three institutions. This study bridges the gap between resource allocation and student psychological outcomes. The robust dual-mediation pathway offers actionable insights for universities: to build student confidence in AI, investments must be channeled not merely into infrastructure but also into pedagogical strategies that demonstrably reduce the perceived complexity of AI tools and illustrate the professional relevance of these tools. Limitations concerning the cross-sectional self-report design and the single-country sample are discussed.

Keywords: Marketing Education, Artificial Intelligence (AI), Technology Acceptance Model (TAM), Dual-Mediation Mechanism

1. Introduction

The rapid advancement of artificial intelligence (AI) and big data technologies is fundamentally transforming marketing practice. The World Economic Forum (2023) identifies AI and big data as among the most consequential drivers of business innovation, while UNESCO (2023) emphasizes that digital transformation in education is simultaneously an opportunity and a source of inequality. For marketing education, this means that graduates must acquire not only traditional strategic competences but also the confidence to deploy AI tools in real decision-making. AI proficiency is a competitive asset in the graduate labor market (Chinchanachokchai et al., 2025).

Although there is broad agreement on the importance of AI adoption in education, empirical research at the micro level remains limited. Specifically, evidence is scarce on how university-provided AI resources and support affect marketing students' practical competencies and their willingness to deploy AI tools. Recent studies have explored future work skills in the AI era (e.g., Chinchanachokchai, 2025) and innovative pedagogies such as project-based learning (e.g., Liao, 2025). However, these efforts tend to be fragmented and lack a theoretical framework that links institutional support to student learning outcomes. In particular, the Technology Acceptance Model (TAM)—a widely used lens for understanding technology adoption—has rarely been applied in this educational context, leaving cross-cultural and contextual variations underexplored.

Our study fills these gaps by empirically examining how students' perceptions of university-supported AI affect technology adoption, extending TAM. Practically, it identifies AI support aspects boosting student confidence, informing resource allocation and policy for business schools, and supporting the UN SDGs for quality education.

This study makes three contributions. Theoretically, it extends TAM into the domain of AI-powered business education, offering a model for understanding institutional empowerment. Practically, it provides actionable guidance for business schools regarding resource allocation and educational policy. Socially, it aligns with the United Nations Sustainable Development Goals (SDGs) by supporting equitable, quality education for an AI-ready workforce.

The remainder of this paper is organized as follows. Section 2 provides a review of relevant literature and develops the hypotheses. Section 3 details the methodology, including sampling, measurement, and analytical procedures. Section 4 presents the results, followed by a discussion in Section 5. Finally, Section 6 concludes with implications, limitations, and suggestions for future research.

Two research questions guide the study. RQ1. How does perceived university support relate to marketing students' AI self-efficacy, and are the effects transmitted through the cognitive beliefs of perceived usefulness and perceived ease of use? RQ2. Does this dual-mediation mechanism operate equivalently across institutionally heterogeneous settings, or do the direct and mediated paths differ across universities?

2. Literature Review

2.1 AI in Higher Education: Institutional Adoption and Structural Enablers

Higher education institutions have moved rapidly from piloting AI tools to embedding them in core provision.

In a systematic review of 138 studies, Crompton and Burke (2023) show that AI in higher education is used chiefly for assessment and evaluation, prediction, and AI assistance, intelligent tutoring, and the management of student learning, with language learning the most frequently studied domain. The review also identifies substantial gaps, among them limited outcome evidence and the near-absence of research on emerging generative tools. Holmes and Tuomi (2022) argue that sustainable adoption depends less on acquiring tools than on data governance, teacher capability, and ethical procurement, while UNESCO (2023) warns that technology deployed without pedagogical purpose can widen existing divides. Dwivedi et al. (2023), drawing on multidisciplinary perspectives on ChatGPT, highlight the disruptive impact of generative AI on assessment integrity and instructional design.

Two implications for this study follow from that literature. Institutional provision is, first, a necessary but insufficient condition for student capability: identical infrastructure can yield markedly different learner outcomes. Second, because institutions differ in governance quality, faculty readiness, and industry linkage, research must model institutional context as a measurable antecedent rather than as a background assumption.

2.2 AI in Marketing Education: From Tool Exposure to Competency

Marketing education faces a distinctive challenge: AI enters the curriculum not as a general productivity tool but as an instrument for analyzing consumer data, generating campaign content, and automating customer-relationship workflows. The field's own journals have begun to treat AI as a curricular imperative rather than a specialist topic (Schlegelmilch & Mills, 2025). Chinchanchokchai et al. (2025) propose a pedagogy-and-competency framework in which generative AI is integrated across the marketing curriculum rather than taught as a stand-alone technology, and Beninger et al. (2025) argue that curriculum-embedded interventions are necessary precisely because the technology itself continues to change. Mehmet et al. (2025) reframe the curriculum around career readiness in the generative-AI era. Alongside this competency turn, AI literacy has consolidated as an explicit educational target (Ng et al., 2021; Almatrafi et al., 2024), although it is typically treated as has a knowledge outcome rather than as a belief about one's own capability. Gonsalves et al. (2026) drawing on practitioner interviews, identify voice, judgment, and taste as the non-delegable human capabilities that AI-rich marketing work still requires, implying that curricula must develop evaluative confidence alongside tool fluency. Russell et al. (2026) show that marketing students discriminate between AI-generated and instructor feedback, which means that the perceived quality of institutional AI provision shapes student engagement with it. Edelblum (2026) demonstrates that data-oriented interventions can reduce the anxiety that dissuades marketing students from analytic tasks.

This literature converges on a competence-development logic: exposure to AI tools does not by itself produce capability; what matters is whether students come to see the tools as usable, relevant to their professional tasks, and within their control. That claim is a psychological one, and it requires an explicit theory of belief formation.

2.3 Theoretical Foundation: TAM, Institutional Support, and Belief Formation

TAM posits that perceived usefulness (PU), defined as the degree to which a person believes that using a system will enhance task performance, and perceived ease of use (PEOU), defined as the degree to which a person believes that using the system will be free of effort, jointly shape technology acceptance, with PEOU also influencing PU (Davis, 1989).

Venkatesh and Davis (2000) show that these beliefs are socially constructed: they are informed by the information available in the user's environment. Venkatesh (2000) further demonstrates that PEOU is anchored in control beliefs and anxiety reduction, which makes it especially sensitive to training and support.

Recent AI-education applications confirm the robustness of these relationships. A meta-analysis of 27 AI-in-education studies reports consistently strong TAM paths (Xue et al., 2026), and Karan and Chakma (2025) replicate the model with 405 higher-education respondents. Mogaji et al. (2024) nevertheless caution that TAM is individual-centric and static, and recommend embedding it in a specific institutional context, the strategy adopted here.

That context is supplied by organizational support theory (Eisenberger et al., 1986), and its perceived-provision component is formed by higher-education evidence that students' appraisals of institutionally provided e-learning shape their satisfaction, behavioral intention, and perceived effectiveness (Liaw, 2008) and that institutional online provision shapes learners' engagement and persistence (Jung & Lee, 2018). It also aligns with evidence that students' perceptions of institutional training provision shape AI adoption (Parra et al., 2024). Grounding PUS in organizational support theory specifies why the construct should matter: perceived support signals institutional commitment and therefore informs the cognitive appraisal of a technology, rather than acting as a diffuse environmental input.

2.4 AI self-efficacy: Conceptualization and Antecedents

Drawing on Bandura (1977), self-efficacy reflects one's confidence in successfully applying AI to marketing tasks, serving as a proximal and sensitive indicator of educational support effectiveness. AI self-efficacy (AISE) is accordingly defined here as a marketing student's belief in their capability to apply AI tools to core marketing tasks, for example, segmenting a market or interpreting consumer data.

AI self-efficacy refers to a student's belief in their capability to successfully use AI tools to solve marketing problems. Research on computer and internet self-efficacy provides the measurement lineage: Compeau and Higgins (1995) developed and validated a computer self-efficacy, Agarwal et al. (2000) distinguished general from software-specific self-efficacy, and Torkzadeh and Van Dyke (2002) showed that training significantly raises internet self-efficacy, confirming that efficacy beliefs are learnable rather than dispositional.

Recent work in AI contexts supports the same logic. Schutte and Li (2025) find that self-efficacy for AI use is associated with greater AI use and mediates the link between curiosity and use; Kim and Lee (2024) show that self-efficacy in AI learning buffers the stress that accompanies organizational AI adoption; Rodríguez-Ruiz et al. (2024) report that self-efficacy is associated with how students deploy AI for academic tasks.

The dual mediators—perceived usefulness and perceived ease of use—then transmit the effect of institutional support to students' AI self-efficacy. This framework not only fills the empirical gap but also reconciles macro and micro perspectives.

2.5 Hypotheses and Conceptual Framework

Combining the two literatures yields a dual-mediation model in which PUS is an exogenous institutional antecedent, PU and PEOU are cognitive mediators, and AISE is the outcome. We advance five hypotheses.

H1. PUS has a positive direct effect on marketing students' AISE.

H2. PU mediates the relationship between PUS and AISE.

H3. PEOU mediates the relationship between PUS and AISE.

H4. PU and PEOU complementarily mediate the PUS–AISE relationship, such that the direct PUS → AISE path remains significant when both mediators are included and the indirect effect via PEOU exceeds that via PU.

H5. The indirect (mediated) paths of the dual-mediation mechanism are invariant across institutionally heterogeneous settings, whereas the direct PUS → AISE path may vary across settings.

H1 follows from the signaling logic of organizational support: perceived institutional commitment raises efficacy independently of specific technology beliefs (Eisenberger et al., 1986; Parra et al., 2024).

The rationale for H2 is that institutional provision demonstrating professional relevance raises utility beliefs, which in turn inform confidence (Davis, 1989; Venkatesh & Davis, 2000).

University support enhances efficacy by shaping beliefs that AI improves marketing outcomes (e.g., deeper consumer insights, campaign personalization). When students observe relevant applications in coursework and faculty examples, they recognize AI's practical value and develop greater confidence in using it.

Perceived ease of use (PEOU) of AI tools mediates the effect of university support on students' AI self-efficacy. H3 rests on evidence that training, accessible tooling, and responsive technical assistance lower effort and anxiety

perceptions, which are proximal determinants of efficacy (Venkatesh, 2000; Torkzadeh & Van Dyke, 2002). Practical training, software access, and tutorials lower perceived complexity and effort; as AI tools become more usable, anxiety drops and confidence in learning and performing with AI increases. H4 follows from the fact that both mediators are present simultaneously, so the appropriate expectation is complementary rather than full mediation. H5 reflects the institutional heterogeneity documented in Section 2.1: measurement and structural equivalence cannot be assumed and must be tested.

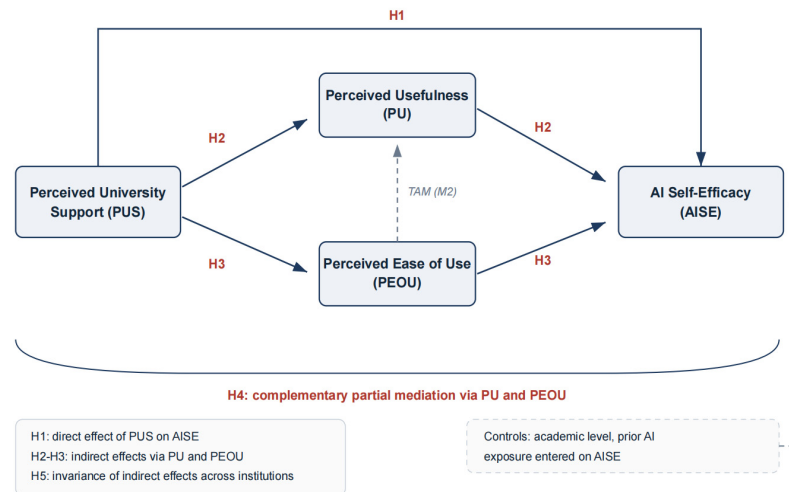


Figure 1. Conceptual model and hypothesized relationships

3. Methodology

3.1 Design and Objectives

This study adopted a cross-sectional survey design to test the dual-mediation model specified in Section 2.5. The design pursues three objectives corresponding to RQ1 and RQ2: (i) to establish the baseline associations among PUS, PU, PEOU and AISE; (ii) to test the direct and mediated paths simultaneously within a latent-variable framework; and (iii) to evaluate whether the estimated structure is invariant across institutionally heterogeneous settings. A cross-sectional design was chosen because it permits efficient collection of large-scale latent-variable data and provides the empirical baseline for later longitudinal or experimental work; its causal limitations are acknowledged in Section 5.5.

3.2 Participants and Sampling

Data was collected between March and April 2025, over a six-week period, through a secure, university-approved online survey platform (Wjx) that supported anonymous distribution and secure data storage. Collection proceeded after the study protocol had been reviewed, approved and registered, as described in Section 3.5. A total of 687 responses were received. After rigorous data cleaning (detailed in the Findings section), the final valid sample was $N = 538$, representing a valid response rate of 78.3%. Participants were recruited using purposive sampling, which was appropriate for testing our proposed model (RQ2). Three universities were selected to reflect diversity in geographic location, institutional type (comprehensive vs. technological), and resource endowment, thereby covering a broad range of perceived support. Respondents were students majoring in marketing or business program at the participating institutions.

3.3 Statistical Power

Sample size requirements were first determined through structural equation modeling power analysis in G*Power (Faul et al., 2007). With a medium effect size ($f^2 = 0.15$; Cohen, 1988), power = 0.80, $\alpha = 0.05$, and a complex model with three latent predictors, G*Power indicated a minimum sample of $N = 300$. To account for possible non-response and ensure stable parameter estimates, the target sample was set at 400–500 students; the achieved $N = 538$ exceeds this target in every subsample ($n = 175$ – 187), so the model is adequately powered both overall and for multigroup estimation.

3.4 Measures and Instrument Adaptation

All multi-item scales used a 7-point Likert format (1 = Strongly Disagree to 7 = Strongly Agree) to enhance sensitivity and variance. The questionnaire included a demographic section and a filter question confirming that participants were active marketing students.

Perceived usefulness (PU) and perceived ease of use (PEOU) were based on Davis's (1989) TAM scale and contextualized for AI marketing tasks (e.g., "Using AI would enable me to analyze consumer data more efficiently"). The perceived

university support (PUS) scale integrated dimensions from Liaw (2008) and Jung and Lee (2018), with a unique item (PUS8) reflecting Chinese industry–education integration; its design referenced literature on educational support systems and technology integration (e.g., resource access, curriculum integration, teaching support). AI application self-efficacy (AISE) was measured with a domain-specific self-efficacy scale modeled on Bandura's (1977) approach and built on Compeau and Higgins's (1995) computer self-efficacy framework, extended to core AI marketing tasks (e.g., "I am confident in my ability to use AI software to segment a market for a new product"). Item development involved a review of relevant literature (e.g., institutional enablers in Liao, 2025) and expert review by two academics specializing in marketing education and educational technology to establish content validity.

Translation and back-translation. Because the instrument was administered in Chinese while the master version was prepared in English, the adapted items were translated using the back-translation procedure recommended by Brislin (1970). Two bilingual researchers in marketing education independently forward-translated the English items into Chinese. A third bilingual translator, blind to the original English items, then back-translated the Chinese version into English. A panel of three experts (two in marketing education and one in educational measurement) compared the back-translations with the original items and retained, for each item, the wording closest to the source construct definition. The reconciled version was then pre-tested as described below. The bilingual instrument, including item wordings, response anchors and item-level source lineage, is reproduced in Appendix A.

Pilot study. A pilot test was conducted with 31 students drawn from all three participating institutions (University A, $n = 11$; College B, $n = 10$; College C, $n = 10$) in March 2025, after the study protocol had been approved and before the main data collection; these respondents are not included in the 687 responses reported in Sections 3.2 and 4.1. The pilot assessed item clarity through respondent debriefing, reliability against a pre-specified criterion of Cronbach's $\alpha > .70$, and completion time. Mean completion time was 11.5 minutes ($SD = 5.2$), within the 10–15 minute administration window pre-specified for the instrument (Appendix A.1), and the reliability coefficients were .76, .81, .74 and .84 for PUS, PU, PEOU and AISE respectively, all above the criterion. Because a pilot of $n = 31$ yields unstable reliability estimates, the pilot coefficients are reported as a screening criterion for item retention rather than as estimates of the reliability of the fielded instrument, which is reported in Table 3. The main established scales cited are shown in Table 1, and the full instrument, with item wordings and response anchors, is reproduced in Supplementary Appendix A.

Table 1. Measurement instrument, source lineage and adaptation

Scale	Items	Construct	Source lineage	Adaptation
PUS	8	Perceived university support	Liaw (2008); Jung and Lee (2018); Eisenberger et al. (1986)	Resource access, curriculum integration, teaching and training support, industry linkage
PU	7	Perceived usefulness	Davis (1989); Venkatesh and Davis (2000)	Re-worded for AI-mediated marketing tasks (consumer analytics, segmentation, personalization)
PEOU	6	Perceived ease of use	Davis (1989); Venkatesh (2000)	Re-worded for generative and analytic AI tools
AISE	7	AI self-efficacy for marketing tasks	Compeau and Higgins (1995); Agarwal et al. (2000); Torkzadeh and Van Dyke (2002)	Domain-specific re-wording for core marketing tasks

3.5 Ethics and Consent

Invitations, informed consent forms, and questionnaire links were distributed through university marketing faculty contacts and relevant student association networks. The survey opened with a participant information sheet explaining the study's objective, the voluntary nature of participation, the anonymity protections, the intended use of the data and the arrangements for questions; the participant information sheet and consent wording are reproduced in Supplementary Appendix C.

Research ethics. The study was conducted in accordance with the principles of the Declaration of Helsinki and with internationally recognized ethical guidelines for educational research. It was a non-interventional, anonymous questionnaire survey of adult students. Because it used anonymized information data, caused no harm to the human body, and involved no sensitive personal information or commercial interest, it falls within the category that is exempt from ethical review under Article 32 of the Measures for the Ethical Review of Life Science and Medical Research Involving Humans (2023). The author's institution does not operate a standing institutional review board or research ethics committee for non-medical social science research, and no ethics review protocol number is therefore applicable. In place of committee review, the study protocol—the questionnaire content, the informed-consent procedure described in Appendix C.2 and the data-protection measures—was reviewed and approved for conduct by the School of Business and registered with the Academic Committee of Yang-en University, which is the university's academic governance body rather than an ethics review committee; the certificate, dated March 5, 2025, is reproduced as Supplementary Appendix D and is available to the editorial office on request. Institutional certification of this kind is not equivalent to formal ethics committee review, and it is reported as a limitation of the institutional context.

Informed consent. Consent was affirmative and required. Respondents read the information sheet and had to select the statement "I have read the information sheet and I agree to participate" before they could enter the questionnaire; respondents who did not select it were routed out of the survey, and no data were recorded from them. Completed questionnaires were not treated as implied consent at any stage.

Participant protections. Three protections are documented in turn. First, consent was affirmative and specific, as described above. Second, the design protected privacy: no names, student numbers, email addresses, IP addresses or other personally identifying information were collected, responses were stored on encrypted, password-protected institutional servers, and results are reported only in aggregate form. Third, respondents retained control over their data: they could skip any item or close the browser at any point without giving a reason, and they could withdraw their responses up to the point of analysis by quoting the anonymous code issued on submission; because responses are anonymous, individual questionnaires can no longer be identified and removed once analysis has begun. Neither this section nor Appendix C contains direct contact information for the research team; questions are directed to the corresponding author through the journal's editorial office.

3.6 Analytical Strategy

Structural equation modeling was carried out in Mplus 8.8; preliminary data management and descriptive statistics were conducted in SPSS 28.0. The analysis followed established best practices. First, data were cleaned and screened by examining missing-data (below 1% per item), identifying multivariate outliers via Mahalanobis distance, and checking normality; missing values were handled with full information maximum likelihood (FIML). Second, descriptive statistics (means, standard deviations, and bivariate correlations) were computed for all variables, and internal consistency was assessed with Cronbach's alpha and composite reliability. Third, confirmatory factor analysis (CFA) tested the hypothesized four-construct model: PUS, PU, PEOU and AISE. Model fit was evaluated using multiple indices (Hu & Bentler, 1999): $\chi^2 / df < 3$, CFI $> .90$, TLI $> .90$, and RMSEA $< .08$.

Following the two-step approach of Anderson and Gerbing (1988), a confirmatory factor analysis (CFA) of the four-factor measurement model (PUS, PU, PEOU, AISE) was estimated. To preserve an adequate parameter-to-observation ratio in a multigroup specification, all confirmatory, invariance and structural models were estimated on 19 within-construct parcels rather than on the 28 individual items; the composition and rationale of the parcels are documented in Appendix B.7, and item-level reliability for the full scales is reported in Table 3. Reliability was assessed with Cronbach's α and composite reliability ($CR \geq .70$); convergent validity with average variance extracted ($AVE \geq .50$); and discriminant validity with the Fornell–Larcker criterion (Fornell & Larcker, 1981), supplemented by the heterotrait–monotrait ratio (HTMT $< .85$). Invariance across institutions was tested in the four-step sequence reported in Section 4.3, and structural paths were compared across groups in a multigroup structural model, with bias-corrected bootstrap confidence intervals used for the indirect effects.

3.7 Common Method Bias

Procedurally, the questionnaire guaranteed anonymity, featured clear and readable items, and organized items into construct-specific blocks (Podsakoff et al., 2003). Statistically, Harman's single-factor test was conducted. The unrotated first factor accounted for 28.7% of the total variance, well below the 50% threshold conventionally regarded as indicative of serious bias. Because this test is only a diagnostic screen, we additionally estimated a single-factor confirmatory model in which all 19 parcels loaded on one common factor. This model fitted the data poorly, $\chi^2(152) = 550.00$, CFI = .83, RMSEA = .070, and substantially worse than the hypothesized four-factor model ($\chi^2(146) = 298.76$, CFI = .968, RMSEA = .044); the difference between the two specifications is significant, $\Delta\chi^2(6) = 251.24$, $p < .001$, indicating that common method variance is unlikely to account for the observed relationships. The syntax for the single-factor model is reproduced as Appendix B, Syntax B-6.

4. Results

4.1 Data Screening and Descriptive Overview

Data collection via an online survey (March–April 2025) yielded 687 initial responses from three universities in China, purposively selected to represent diverse institutional profiles. After rigorous screening—excluding cases with completion time below one-third of the median completion time, patterned responses, or more than 20% missing data on core scales—a final valid sample of $N = 538$ was retained (valid response rate = 78.3%). Regional distribution was balanced: University A ($n = 187$, 34.8%), College B ($n = 176$, 32.7%), and College C ($n = 175$, 32.5%). Demographic characteristics and regional comparisons are summarized in Table 2. Academic level and prior AI exposure, which exhibited significant regional variation, were included as control variables in all subsequent analyses.

4.2 Measurement Model Assessment

The demographic characteristics of the final sample are presented in Table 2.

Table 2. Sample Demographics by Region (N=538)

Characteristic	University A (n=187)	College B (n=176)	College C (n=175)	Total (N=538)	Test Statistic (χ^2)
Gender					3.21 (p=.201)
- Male	45.5% (85)	40.3% (71)	42.9% (75)	42.9% (231)	
- Female	54.5% (102)	59.7% (105)	57.1% (100)	57.1% (307)	
Academic Level					18.42 (p=.001)
- Year 1-2	15.0% (28)	10.2% (18)	18.3% (32)	14.5% (78)	
- Year 3-4	55.6% (104)	48.9% (86)	52.0% (91)	52.2% (281)	
- Postgraduate	29.4% (55)	40.9% (72)	29.7% (52)	33.3% (179)	
Prior AI Exposure					25.67 (p < .001)
- Low	22.5% (42)	38.6% (68)	25.1% (44)	28.6% (154)	
- Moderate	48.1% (90)	45.5% (80)	45.1% (79)	46.3% (249)	
- High	29.4% (55)	15.9% (28)	29.7% (52)	25.1% (135)	

Before testing structural paths, confirmatory factor analysis (CFA) was conducted to evaluate the hypothesized four-factor measurement model (PUS, PU, PEOU, AISE), estimated on 19 within-construct parcels (Appendix B.7). The model demonstrated excellent fit to the data: $\chi^2(146) = 298.76$, $p < .001$, CFI = .968, TLI = .962, RMSEA = .044 (90% CI [.037, .051]), SRMR = .038. All factor loadings were significant ($p < .001$) and substantial, ranging from .68 to .89. Internal consistency reliability was satisfactory across constructs and regions (Cronbach's $\alpha > .85$; Composite Reliability $> .89$). Convergent validity was established, as all Average Variance Extracted (AVE) values exceeded .50 (range: .62-.76). Discriminant validity was confirmed: the square root of the AVE for each construct exceeded its correlations with all other constructs.

Table 3. Scale Reliability and Convergent Validity by Region

Construct	Region	Cronbach's α (28 items)	Composite Reliability (CR) (19 parcels)	Average Variance Extracted (AVE) (19 parcels)
Perceived University Support (PUS)	University A	.89	.92	.68
	College B	.87	.90	.65
	College C	.88	.91	.67
Perceived Usefulness (PU)	University A	.91	.94	.75
	College B	.88	.91	.72
	College C	.90	.93	.73
Perceived Ease of Use (PEOU)	University A	.86	.90	.64
	College B	.85	.89	.62
	College C	.87	.91	.66
AI Application Self-Efficacy (AISE)	University A	.92	.95	.76
	College B	.90	.93	.73
	College C	.91	.94	.75

Note. Cronbach's alpha is computed on the 28 individual items; composite reliability (CR) and average variance extracted (AVE) are computed in the 19-parcel measurement model used for the confirmatory, invariance and structural analyses (Appendix B.7). The diagonal of Table 4 reports the square roots of the parcel-level AVE values.

Table 4. Descriptive Statistics and Intercorrelations of Study Variables by Region

Region	Variable	M	SD	1	2	3	4
University A (n=187)	1. PUS	4.65	1.01	(.82)			
	2. PU	5.22	0.89	.51**	(.87)		
	3. PEOU	4.95	0.98	.48**	.62**	(.80)	
	4. AISE	4.88	1.05	.43**	.59**	.66**	(.87)
College B (n=176)	1. PUS	4.41	1.12	(.81)			
	2. PU	5.15	0.94	.55**	(.85)		
	3. PEOU	4.62	1.05	.52**	.58**	(.79)	
	4. AISE	4.79	1.10	.46**	.55**	.63**	(.85)
College C (n=175)	1. PUS	4.82	1.08	(.82)			
	2. PU	5.18	0.91	.49**	(.85)		
	3. PEOU	4.78	1.02	.45**	.60**	(.81)	
	4. AISE	4.91	1.02	.41**	.57**	.61**	(.87)

Note: ** $p < .01$. Diagonal values (in parentheses) are the square root of the AVE for each construct. M = Mean, SD = Standard Deviation. PUS = Perceived University Support, PU = Perceived Usefulness, PEOU = Perceived Ease of Use, SE = Self-Efficacy.

4.3 Measurement Invariance

To ensure meaningful cross-group comparisons, a multigroup confirmatory factor analysis was performed. The configural model, in which the factor structure was freely estimated within each institution, fitted the data well, $\chi^2(438) = 645.21$, CFI = .961, RMSEA = .030, indicating that the same four-factor structure was tenable across institution. Constraining the factor loadings to equality did not significantly degrade fit, $\Delta\chi^2(20) = 28.34$, $p = .101$; $\Delta\text{CFI} = -.002$; $\Delta\text{RMSEA} = -.001$, supporting metric invariance. For the scalar model, the scaled difference test (Satorra & Bentler, 2009) indicated a

significant decrement, $\Delta\chi^2(34) = 78.65$, $p < .001$, whereas the change in fit indices remained within the conventional criteria ($\Delta CFI = -.008$; $\Delta RMSEA = .002$). Because the χ^2 difference test is sensitive to sample size and model complexity and can detect a small number of non-invariant parameters that leave global fit indices largely unaffected (Cheung & Rensvold, 2002), the divergence between the two sets of criteria was treated as evidence that at least some parcel intercepts are not invariant across institutions. We therefore adopted a conservative position and did not treat full scalar invariance as established. A partial scalar model was estimated in which two parcel intercepts were freely estimated - one in the College B sample and one in the College C sample ($\Delta df = 2$). This model fitted the data acceptably, $\chi^2(490) = 690.28$, $CFI = .955$, $RMSEA = .028$, and did not differ significantly from the metric model, $\Delta\chi^2(32) = 38.41$, $p = .204$; $\Delta CFI = -.004$; $\Delta RMSEA = -.001$, providing a sufficient basis for comparing structural paths across institutions. Table 5 summarizes the sequence.

Table 5. Tests of measurement invariance across institutions

Model	χ^2 (df)	CFI	RMSEA	Comparison	Scaled $\Delta\chi^2$ (Δdf)	p	ΔCFI	$\Delta RMSEA$	Decision
Configural	645.21 (438)	.961	.030	—	—	—	—	—	Accept
Metric	661.87 (458)	.959	.029	vs. configural	28.34 (20)	.101	-.002	-.001	Accept
Scalar	740.52 (492)	.951	.031	vs. metric	78.65 (34)	< .001	-.008	+.002	Not established
Partial scalar (2 intercepts freed)	690.28 (490)	.955	.028	vs. metric	38.41 (32)	.204	-.004	-.001	Accept

Note. The models are specified on 19 parcels per group; see Appendix B.7 for the composition of the parcels. χ^2 values are the Satorra–Bentler scaled statistics; the $\Delta\chi^2$ test was computed with the scaled difference test (Satorra & Bentler, 2009). RMSEA values are those implied by the reported χ^2 , df and $N = 538$.

We note that the item-level identity of the two freed intercepts could not be recovered from the archived estimation output; We report this transparently rather than reconstructing it. This omission does not affect the substantive conclusions, for two reasons. First, the cross-group comparisons central to this study concern structural paths rather than parcel-level or latent mean differences, and the partial scalar model was statistically indistinguishable from the metric model, $\Delta\chi^2(32) = 38.41$, $p = .204$, so the pattern of structural estimates is insensitive to which intercepts are freed. Second, the identity of non-invariant intercepts bears primarily on the interpretation of latent mean differences, which this study does not estimate. Section 5.5 records this as a reporting limitation.

4.4 Descriptive Statistics and Regional Mean Differences

Means, standard deviations, and intercorrelations are presented in Table 4. All variables were significantly and positively correlated ($r = .41-.66$, $p < .01$), providing preliminary support for the hypothesized relationships.

A one-way MANOVA revealed significant regional differences (Wilks' $\Lambda = .92$, $F(8, 1064) = 5.43$, $p < .001$). Univariate ANOVAs indicated significant differences for PUS ($F(2, 535) = 7.12$, $p = .001$, $\eta^2 = .026$) and PEOU ($F(2, 535) = 4.05$, $p = .018$, $\eta^2 = .015$). Post-hoc Tukey HSD tests showed that College B students reported significantly lower PUS than College C ($p = .002$), while University A students reported higher PEOU than College B students ($p = .012$). No significant regional differences emerged for PU or SE.

4.5 Structural Model and Hypothesis Testing

The hypothesized structural model was estimated using multigroup structural equation modeling with robust maximum likelihood (MLR). The unconstrained model (structural paths free to vary) fit the data well: $\chi^2(420) = 815.40$, $p < .001$, $CFI = .958$, $TLI = .952$, $RMSEA = .042$ (90% CI [.036, .047]), $SRMR = .045$. Standardized path coefficients and indirect effects (bias-corrected bootstrap, 5000 resamples) are summarized in Table 6. and the structural model is presented graphically in Figure 2.

Table 6. MultiGroup Structural Equation Modeling Results (Standardized Estimates)

Path	University A (n=187)	College B (n=176)	College C (n=175)
Direct Effects			
PUS → Self-Efficacy (AISE)	.15* (.06)	.18** (.06)	.10 (.06)
PUS → Perceived Usefulness (PU)	.51*** (.06)	.55*** (.06)	.49*** (.06)
PUS → Perceived Ease of Use (PEOU)	.48*** (.06)	.52*** (.06)	.45*** (.07)
PU → Self-Efficacy (AISE)	.28*** (.07)	.22** (.08)	.31*** (.07)
PEOU → Self-Efficacy (AISE)	.45*** (.07)	.48*** (.07)	.40*** (.07)
Control Variables			
Academic Level → AISE	.09 (.05)	.11* (.05)	.08 (.05)
Prior Exposure → AISE	.21*** (.05)	.17** (.06)	.19*** (.05)
Indirect Effects (Bootstrap)			
PUS → PU → AISE (H2)	.14** [.06, .23]	.12* [.04, .21]	.15** [.07, .24]
PUS → PEOU → AISE (H3)	.22*** [.13, .31]	.25*** [.16, .34]	.18** [.09, .28]
Total Effect (PUS → AISE)	.51***	.55***	.43***
R ² for Self-Efficacy	.58	.56	.54

Note: Standard errors in parentheses for direct paths. Bootstrap 95% confidence intervals in brackets for indirect effects. * $p < .05$, ** $p < .01$, *** $p < .001$. PUS = Perceived University Support.

4.5.1 Direct Effects (H1)

The direct effect of perceived university support (PUS) on self-efficacy (AISE) was significant for University A and College B, but not for College C. A Wald test comparing College B and College C was marginally significant ($\chi^2(1) = 3.84$, $p = .050$). H1 therefore received partial support, suggesting that the direct psychological empowerment effect of PUS may be context-dependent.

4.5.2 Indirect Effects via Perceived Usefulness (H2)

The indirect effect of PUS on AISE through perceived usefulness (PU) was significant in all three samples. Equality constraints across groups were non-significant ($\chi^2(2) = 0.47$, $p = .791$), supporting H2 and confirming the stability of this mediation path across institutional contexts.

4.5.3 Indirect Effects via Perceived Ease of Use (H3)

The indirect effect via perceived ease of use (PEOU) was consistently significant across all three samples. Cross-group differences were non-significant ($\chi^2(2) = 1.82$, $p = .403$), fully supporting H3. Across all subsamples, the PEOU-mediated effect was larger than the PU-mediated effect.

4.5.4 Total Effects and Model Explanatory Power

The total effect of PUS on AISE (direct plus indirect) was significant and substantial across institutions ($\beta = .43-.55$). Among control variables, prior AI exposure significantly predicted SE in all samples, whereas academic level was only marginally significant in College B. The model explained 54–58% of the variance in marketing students' AI self-efficacy ($R^2 = .54-.58$), indicating strong explanatory power.

Figure2. Structural equation model

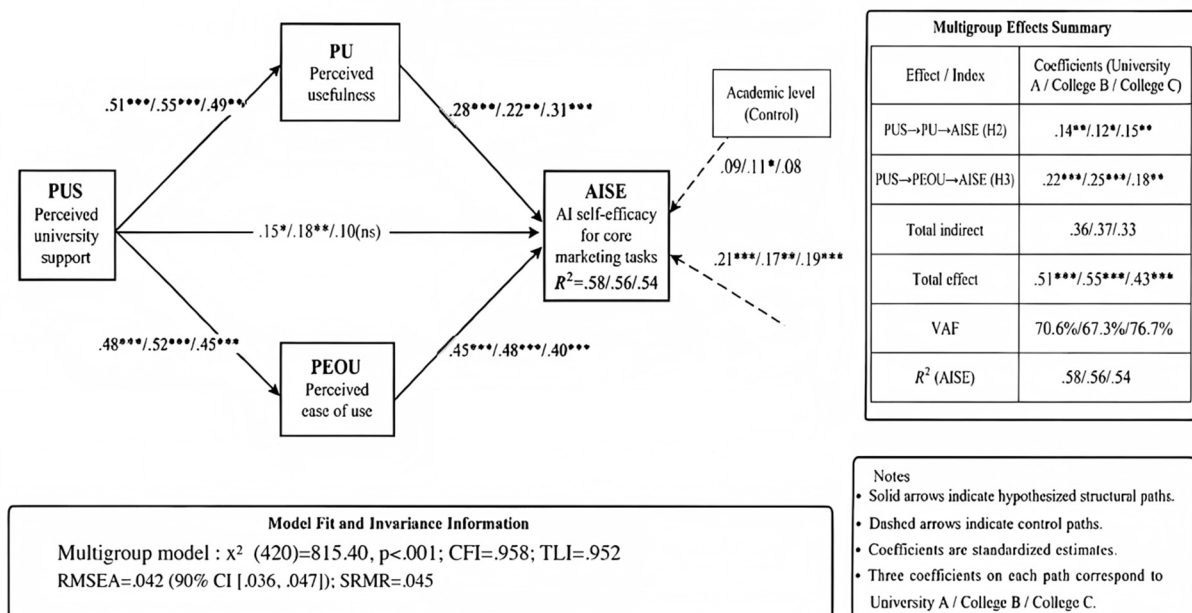


Figure 2. Model of analyzing path and conclusion

5. Discussion

5.1 Interpretation of Findings

The direct path from PUS to AISE was context-dependent—significant in two of three samples—whereas both indirect paths were robust across all institutional samples. The consistency of these indirect effects, despite mean-level regional differences, indicates that perceived usefulness and perceived ease of use are the central mechanisms linking institutional support to AI self-efficacy, a pattern consistent with mediation. The consistent superiority of the PEOU pathway has a clear social-cognitive reading. Marketing students typically approach AI with limited formal computational training, so algorithmic complexity is experienced as a threat rather than a challenge; when perceived effort is high, self-efficacy judgments are made under conditions of anxiety, which depresses efficacy appraisal regardless of how useful the tool is believed to be. PEOU therefore functions as a cognitive gatekeeper: only once the tool appears manageable does evidence

of its usefulness become informative for confidence. This interpretation is consistent with Venkatesh's (2000) anchoring-and-adjustment account of PEOU and with recent evidence that efficacy beliefs mediate the relationship between student dispositions and AI use (Schutte & Li, 2025).

5.2 Theoretical Contributions

This study makes three non-overlapping contributions. First, it extends the Technology Acceptance Model (TAM) from behavioral prediction to psychological competency formation. Second, it specifies the exogenous construct theoretically: by grounding PUS in organizational support theory (Eisenberger et al., 1986) and measurement lineage in higher education support research (Liaw, 2008; Jung & Lee, 2018), it replaces the unspecified 'external variable' of TAM with a testable institutional antecedent. Third, it establishes an empirical distinction that the literature has conflated: the mediated mechanism is invariant, but the direct empowerment path is context-dependent; this reframes cross-institutional heterogeneity as a property of the direct path rather than of the psychological model, and offers a template for multigroup TAM research in AI education (Xue et al., 2026).

5.3 Comparison with Prior Literature

Our results align with the TAM meta-analytic evidence in AI education, which reports consistently large paths, while going beyond it by locating the mechanism in efficacy formation rather than intention (Xue et al., 2026; Karan & Chakma, 2025). In contrast to the individual-centric and static critiques of TAM (Mogaji et al., 2024), embedding the model in organizational support theory and testing invariance addresses the cultural and contextual applicability gap directly. The PEOU dominance observed here is consistent with recent work showing that self-efficacy for AI use is a proximal driver of AI engagement (Schutte & Li, 2025; Kim & Lee, 2024) and with evidence that self-efficacy shapes how students mobilize AI in academic tasks (Rodríguez-Ruiz et al., 2024). Our findings extend this line by identifying institutional levers (training, technical assistance and scaffolded tooling) that raise those efficacy beliefs, in line with evidence that perceived training provision shapes AI adoption (Parra et al., 2024). Finally, the study connects to marketing education research that identifies evaluative judgment as the irreducibly human capability in AI-mediated work (Gonsalves et al., 2026), shows that AI-related feedback sources matter to student engagement (Russell et al., 2026), and demonstrates that data-oriented pedagogy can reduce the anxiety that blocks analytic skill development (Edelblum, 2026).

5.4 Practical Implications

Universities should not assume that infrastructure investment alone converts into student confidence. The finding that PEOU carries the larger indirect effect implies that the highest-yield intervention is demystification: plain-language onboarding, guided laboratories with low-stakes practice, scaffolded tutorials, peer mentoring and instructor demonstrations that keep perceived effort low. Once effort perception falls, usefulness framing becomes effective — so the second prong, anchoring examples in tasks students will actually perform (segmentation, campaign evaluation, consumer analytics), should follow rather than precede the first. Because the mediated mechanism was invariant while the direct path was not, institutions with weaker baseline provision should additionally exploit the direct signaling channel: visible institutional commitment — lab access, industry projects, dedicated technical support — carries independent efficacy value where cognitive doors are not yet open. Faculty development, therefore, should be treated as a pedagogical investment rather than an IT expense.

5.5 Limitations and Future Research

The cross-sectional design, first, precludes causal inference; although the mediating structure is theoretically ordered, only longitudinal or experimental designs can establish directionality. Second, all measures were self-reported, which raises common method concerns; the procedural and statistical remedies reported in Section 3.7 mitigate but do not eliminate this risk. Third, the sample from three universities in one country limits external validity. Fourth, AI was treated as a monolithic construct, which obscures functional differences between predictive-analytic tools (e.g., statistical modeling environments) and generative tools (e.g., conversational assistants), and between classroom and professional use contexts; disaggregating by tool type and task is a priority for subsequent work. Fifth, our structural model estimated the two indirect paths separately and did not include the PEOU → PU path specified in the original TAM (Davis, 1989; Venkatesh & Davis, 2000). Because PEOU and PU were modeled as correlated mediators rather than as a serial chain, the estimate of the PUS → PU → AISE path does not partial out the influence of PEOU on PU, and the usefulness pathway should therefore be read as a conservative, lower-bound estimate of that mechanism. Estimating the fully specified serial model across institution types is an explicit priority for future research.

6. Conclusion

University support does not translate into marketing students' AI self-efficacy through a single undifferentiated channel. It operates through two routes at once: a direct empowerment effect that signals institutional commitment, and an indirect route through students' beliefs about how easy and how useful AI tools are. Both indirect routes held in all three

institutions, and the ease-of-use route was consistently the stronger of the two — students who feel capable with AI are telling us, first, that the tools seem manageable. The practical reading is therefore twofold. Universities should invest first in reducing friction with AI tools — guided labs, plain-language instructions, low-stakes practice, peer mentoring — and only then in persuading students of their professional usefulness.

Equally telling is the consistency of this dual mediation across institutions. The direct route, by contrast, held in only two of the three institutions, which means that the strength of institutional signaling depends on local baseline conditions. Because the mediated mechanism travels while the direct effect does not, institutions with weaker provision need not adopt a different model, but they do need a more emphatic one. These conclusions are offered subject to the limitations above; cross-national, longitudinal and tool-differentiated designs are the next step.

Declarations

Ethics approval and consent to participate.

This study was conducted in accordance with the ethical principles of the Declaration of Helsinki and with internationally recognized ethical guidelines for educational research. It was a non-interventional, anonymous questionnaire survey of adult university students, involving no clinical or biomedical procedure, no intervention, no deception and no collection of health-related or otherwise sensitive personal data, and it posed no more than minimal risk to participants. Under Article 32 of the Measures for the Ethical Review of Life Science and Medical Research Involving Humans (2023), research of this kind— non-interventional, using anonymized information data, causing no harm to the human body, and involving no sensitive personal information or commercial interest—is exempt from ethical review. The author's institution does not operate a standing institutional review board or research ethics committee for non-medical social science research, and no ethics review protocol number is therefore applicable. In place of committee review, the study protocol was reviewed and approved for conduct by the School of Business and registered with the Academic Committee of Yang-en University on March 5, 2025; the corresponding certificate is reproduced as Supplementary Appendix D and is available to the editorial office on request. Institutional certification of this kind is not equivalent to formal ethics committee review and is reported as a limitation of the institutional context. All participants received a written information sheet stating the purpose of the study, the voluntary nature of participation, the anonymity of responses, the intended use of the data and the arrangements for questions, and participants gave affirmative consent by selecting the statement "I have read the information sheet and I agree to participate" before entering the questionnaire; no implied-consent procedure was used. No personally identifying information was collected, and data were analyzed in aggregate form only. The participant information sheet and consent wording are reproduced in Supplementary Appendix C.

Disclosure Statement

No potential conflict of interest was reported by the author(s).

Supplementary material.

Appendix A: (English/Chinese) survey questionnaire with item wordings and source citations.

Appendix B: codebook, correlation and covariance matrices, invariance detail and Mplus syntax.

Appendix C: participant information sheet and informed consent wording.

Appendix D: institutional approval and registration certificate for the study protocol.

Declaration of generative AI in writing.

During the preparation of this work the authors used NetEase Youdao Translate for language editing and proofreading, and the iCIBA (<https://www.iciba.com/grammar>) for grammar checking and proofreading. The authors reviewed and edited all generated content and take full responsibility for the integrity of the manuscript.

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Author contributions

Yuanmei W.: conceptualized the study and drafted the initial manuscript; Shujuan L.: conducted a systematic literature review, Min H.: handled the methodology; Yuanmei W.: designed the questionnaire and did the discussion of findings; Min H. and Shujuan L.: shared the questionnaire. All authors read and approved the final manuscript.

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Competing interests

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Informed consent

Obtained.

Ethics approval

The Publication Ethics Committee of the Redfame Publishing.

The journal's policies adhere to the Core Practices established by the Committee on Publication Ethics (COPE).

Provenance and peer review

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Data availability statement

The data that support the findings of this study are available on request from the corresponding author. The data are not publicly available due to privacy or ethical restrictions.

Data sharing statement

No additional data are available.

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