Asian Administration and Management Review

Original Research Article

Received: 1 April 2025 **Revised:** 11 May 2025 **Accepted:** 12 May 2025

BRIDGING THE AI DIVIDE: ADOPTION CHALLENGES IN MARKETING EDUCATION IN LAOS

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(This article belongs to the Theme 1: Business & Economic in Industry 5.0)

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Abstract

This study investigates the adoption of Artificial Intelligence (AI) in marketing education among students in Laos, a developing country facing infrastructure and digital literacy challenges. Integrating the Technology Acceptance Model (TAM) and the Theory of Planned Behavior (TPB), with contextual factors like AI literacy, pedagogical alignment, and accessibility, the research examines the factors influencing AI adoption. A quantitative approach was employed, gathering data from 165 marketing students across multiple universities in Laos and analyzing it through Structural Equation Modeling (SEM). Results indicate that perceived usefulness and ease of use significantly shape attitudes toward AI, while behavioral control and accessibility strongly influence adoption intention. Social influence has minimal impact, suggesting adoption decisions are driven by practical utility rather than peer pressure. The study recommends hands-on AI training, user-centric programs, and improved access to AI resources to bridge the digital divide.

Keywords: AI Adoption, Marketing Education, Digital Divide, Technology Acceptance Model (TAM), Theory of Planned Behavior (TPB)

Citation Information: Sirivanh, T., Ladtakoun, S., & Vongsanga, N. (2025). Bridging the AI Divide: Adoption Challenges in Marketing Education in Laos. *Asian Administration and Management Review, 8*(2), Article 6. https://doi.org/10.14456/aamr.2025.31

Introduction

Artificial Intelligence (AI) is changing education around the world with new features such as personalized learning, intelligent tutoring, and content automation, all of which boost student participation and academic performance (Chan, 2023). AI technologies like automated learning systems, software for sentiment analysis, and predictive analytics are changing the relationships that students and educators have with educational materials (Grewal et al., 2025; Singh & Pathania, 2024). AI has unique advantages in marketing education because it allows students to practically engage with decision-making through data, modeling consumer behaviors, and digital advertising (Elhajjar et al., 2021; Koch et al., 2024). Students are now able to apply AI to customer segmentation, automated marketing campaign analytics, and content generation, which is essential for the contemporary business world (Al-Rahmi et al., 2021). Yet, while advanced countries have normalized AI adoption in teaching marketing, integrating this technology into developing countries like Laos is slow and patchy due to technological infrastructure, digital skills, and faculty preparedness (Ha & Chuah, 2023).

While there is an increasing global dependence on AI technologies, the use of AI in education remains strikingly low in Laos (Hu et al., 2020). United Nations Educational, Scientific and Cultural Organization (2023) reports that only 12% of higher education institutions in Laos have integrated AI tools into their programs, which pales in comparison to Thailand's 38% and Vietnam's 41%. A study from Meadley (2023) reports that more than 60% of students in Laos have never used AI tools in their coursework, and only 25% of instructors feel comfortable using AI-learning teaching methodologies. A Lao Ministry of Education and Sports survey conducted in 2022 found that fewer than 15% of university programs offered AI courses, indicating a lack of comprehensive AI education frameworks for marketing. These findings correspond with international studies that highlight the challenges facing developing countries in adopting AI technologies in higher educational institutions, including inadequately trained faculty resources, limited funding, and aged teaching materials (Spais et al., 2024; Zhao et al., 2022). With the integration of AI into business and marketing, Keoamphone (2022) argues that Lao students stand to lose the most as they fall behind their international competitors in acquiring vital skills needed in an automated and data-driven economy.

As the need for AI-enhanced marketing skills in the labor market rises, this research becomes more relevant (Ivanov et al., 2024; Srivastava & Singh, 2023; Zhao et al., 2022). Today, marketing professionals are required to understand AI, including machine learning, predictive analysis, and digital content automation, because businesses worldwide are incorporating AI-powered customer intelligence, automated ad buying systems, and chatbot interactions (Nesterenko & Olefirenko, 2023). Globally, employers highly value graduates possessing skills in leveraging AI for customer relationship management, real-time analytics, and geo-targeting advertising (Richter et al., 2024). Nevertheless, Laos marketing students encounter substantial obstacles in developing these proficiencies, hindering their competitiveness within the global job market. By way of illustration, the integration of AI tools into university programs is notably lower in Laos (12%) than in Thailand (38%) and Vietnam (41%) (United Nations Educational, Scientific and Cultural Organization, 2023). There is a growing expectation among employers that graduates understand how AI assists in managing customer relations, real-time analytics, and geo-targeted advertising (Richter et al., 2024). Unfortunately, for marketing students in Laos who aspire to become competitive in the global job market, numerous obstacles impede the acquisition of these competencies.

The lack of tools and cyber infrastructure digital systems in the universities of Laos presents serious hurdles in Engineering Education (Asian Development Bank, 2021). This translates to numerous educational institutes not having access to technology such as marketing AI instruments, advanced data processing technologies, and cloud computing systems, which would allow students to learn experientially (United Nations Educational, Scientific and

Cultural Organization, 2023). Students outside of these frameworks cannot acquire practical skills in AI technologies, which are increasingly essential for employment in marketing (Elhajjar et al., 2021). Furthermore, the adoption of AI systems is stunted by the lack of basic AI competency among students and tutors (Vlačić et al., 2021). Lack of policy on training in information communication technology, AI-based pedagogy for faculty, and active learning approaches for students contribute to the sluggish adoption rate of AI-empowered educational systems. Many educators are not fully trained in AI methodologies, limiting their ability to effectively incorporate AI-based learning strategies into the curriculum (Dwivedi et al., 2021). Furthermore, blockchain technology does not constitute a fundamental part of marketing education in Laos due to its institutional structural and policy-related issues (Demas et al., 2018). The lack of national policies concerning education and AI technologies, coupled with limited funding directed towards AI initiatives and the scope of private-public collaboration, hinders the adoption of systems AI infrastructure within academia (Asian Development Bank, 2021). Unlike the other nations where the governments have worked in educational transformation, AI integration is actively promoted through national digital transformation policies, but Laos does not have a comprehensive plan for AI usage within higher educational institutes (United Nations Educational, Scientific and Cultural Organization, 2023). Due to this lack of strategic focus, efforts towards AI integration are not systematically directed, which creates inconsistent standards of access to AI learning resources associated with varying institutional resources. (Hennelly & Ctori, 2022).

Another important barrier is the view of AI technology as a threat, not an opportunity (Elhajjar et al., 2021). Some students and educators hold the misconception that AI will take over traditional marketing jobs, which creates a resistance toward its adoption (Grewal et al., 2025). More generally, there is a belief that AI will diminish job opportunities in marketing instead of augmenting professionals' capabilities to analyze sophisticated data, automate menial tasks, and aid in strategic decision making (Rust, 2020). Overcoming this problem requires changing the narrative, as AI's role is to enhance human skills, not replace them (Singh & Pathania, 2024).

In light of these difficulties, this research aims to determine the underlying reasons obstructing AI integration in marketing education in Laos and formulate data-driven proposals that address the digital disparity. Guided by the Technology Acceptance Model (TAM) (Davis, 1985) and the Theory of Planned Behavior (TPB) (Ajzen, 1991), and incorporating AI literacy (AIL), pedagogical alignment (PA), and accessibility (AC) as context-specific factors, this study constructs a model that captures the students' perception of AI about their attitudes, intentions, and participation in teaching marketing courses (Ajzen, 1991; Davis, 1985).

Literature Review

The use of AI technologies worldwide to diversify learning, foster interaction among students, and aid teaching has gained more popularity (Nesterenko & Olefirenko, 2023). In developed countries, AI instructional materials such as adaptive learning technologies, grading bots, and even chatbots are widely used in higher education to facilitate self-paced learning and maximize academic outcomes (Dwivedi et al., 2021; Grewal et al., 2025). The situation is markedly different in developing countries, where the adoption rate is comparatively low because of a lack of technological infrastructure, inadequate training for instructors, and inadequate digital skills of the learners (Asian Development Bank, 2020; United Nations Educational, Scientific and Cultural Organization, 2023). In the context of Laos, these barriers contribute to a gap that prevents learners from gaining critical AI skills that are vital for marketing and business professions in an AI-dominated economy (Hennelly & Ctori, 2022).

Theoretical Frameworks: TPB and TAM in AI Adoption

The incorporation of AI in education is frequently assessed through behavioral intention models that focus on how people interact with innovations. Two common models in technology adoption studies are the TPB (Ajzen, 1991) and the TAM (Davis, 1985). TPB framework that builds on that model by adding sociological and psychological elements (Ajzen, 1991). TPB adds Subjective Norms (SN), Perceived Behavioral Control (PBC), and Attitude Toward Behavior (ATB) to the existing framework of technology adoption. SN describes the role of peers, teachers, and other forms of social and institutional support in students' adoption of AI as technology, while PBC captures students' beliefs about their ability to use AI tools relative to their level of digital skills and resources (Singh & Pathania, 2024). ATB influences the students' willingness to accept AI towards adoption and use, as influenced by the perception of the benefits and convenience (Chai et al., 2021). Studies have shown that an institution's active support and strong subjective norms, accompanied by digital readiness, were factors that increased the adoption of AI (Rust, 2020). The TAM model proposes that an individual's acceptance of a new technology is determined by Perceived Usefulness (PU) and Perceived Ease of Use (PEOU). When applied to AI-powered tools in marketing education, PU corresponds to the students' conviction that AI enhances their learning through better decision-making and analytical skill development, while PEOU signifies the students' perceptions of the ease of use of AI tools for marketing functions (Elhajjar et al., 2021). Research indicates that an increase in PU and PEOU positively impacts the probability of students utilizing AI-enhanced study tools (Hennelly & Ctori, 2022). Regardless of how useful the TPB and TAM are, researchers claim that these frameworks do not attempt to address the issues impeding AI adoption in developing countries (Dwivedi et al., 2021). Henceforth, this research integrates three more aspects to TAM and TPB.

In the context of education, AIL is defined as the knowledge and capability to utilize certain AI functions at a particular level effectively; in this case, at a student level (Du et al., 2024). Koch et al. (2024) argue that AI literacy also means knowing how AI works, what it can do, and the moral issues surrounding it, which is vital for properly servicing the needs of marketing education. Research indicates that the confidence and willingness of students to work with AI-powered platforms for learning increases with the level of AI literacy. Consequently, this results in increased acceptance rates (Zhao et al., 2022). In marketing education, AI literacy enables students to work with predictive analytics, sentiment analysis, and automated digital marketing tools, preparing them for data-driven decision-making in the industry (Chahal & Rani, 2022). Yet, studies underscore that most students from developing countries do not have adequate learning opportunities to interact with AI technologies due to a lack of appropriate curriculum resources and access to AI tools (Hennelly & Ctori, 2022). Thus, strengthening AI literacy is the most effective way to increase the adoption of AI technologies by marketing students in Laos.

MacPhail et al. (2013) define PA as integrating AI tools into the curriculum, instructions, and goals in teaching. Chan (2023) note that AI in education is most effective when it augments rather than replaces traditional teaching practices. In marketing education, this requires that AI tools, including chatbots for customer service role-play, automated content generation, and AI-driven market analysis, are taught within the courses that utilize them (Davenport, 2018). Research indicates that a lack of balance between teaching curricula and AI teaching resources often leads to a hostile reception by both educators and students (Srivastava & Singh, 2023). Students may struggle to understand the relevance of marketing education when AI technologies are inadequately integrated, instructors lack sufficient training, or a pedagogical framework is absent (Hu et al., 2020). For these reasons, it is important to ensure strong pedagogical alignment between AI technologies and the marketing curriculum to enhance the adoption of AI technologies in Laos.

AC incorporates the degree of ease with which AI-powered learning tools can be accessed, including the technological setting, internet access, faculty skills, and infrastructure of a particular region (Ibrahim et al., 2017). For developing countries such as Laos, the lack of digital infrastructure, high costs, and unequal distribution of AI educational resources still make accessibility to AI one of the biggest challenges (Asian Development Bank, 2021; Demas et al., 2018). Research suggests that students who have access to AI learning education tools are more likely to adopt the use of AI in education with the proper motivational support (Bughin et al., 2017). Furthermore, faculty training and preparedness are significant factors in determining how AI can be accessed. In instances where educators do not have the necessary tools and knowledge to integrate AI into lessons, students will be deprived of the exposure to the AI learning tools that are essential for them (Chan, 2023). Addressing accessibility challenges requires investment in digital infrastructure, government policy support, and faculty development programs (Demas et al., 2018).

AI in Marketing Education: Global Trends and Best Practices

AI is transforming the teaching of marketing by fostering student competencies in making data-influenced choices, predictive analytics, and content development through AI technologies (Nesterenko & Olefirenko, 2023; Spais et al., 2024). Many top universities have included automated digital advertising, customer sentiment analysis, and real-time sentiment monitoring using AI in teaching coursework (Chan, 2023; Du et al., 2024). Nevertheless, the implementation of AI in marketing education differs greatly between regions.

Students in North American and European universities have access to fully AI-integrated courses in instructive consumer profiling, brand management simulations, and advanced marketing techniques using deep learning algorithms (Singh & Pathania, 2024). In Asia, and especially in China and Singapore, the adoption of AI in marketing education is bolstered by public policies and thus offers courses focused on AI in marketing, emphasizing customer service through chatbots and machine learning for audience-tailored marketing strategies (Elhajjar et al., 2021). In contrast, developing countries are slow to adopt AI due to financial constraints, insufficient teaching staff, and the threat of AI automation on conventional marketing roles (Demas et al., 2018). These differences underscore the need for proposed AI training programs in economically disadvantaged countries, including Laos.

AI Adoption in Higher Education: The Case of Laos

While the impact of AI on education worldwide is growing rapidly, its adoption in Lao universities is still very low. Based on AI-related courses offered, only 12% of Lao universities incorporate them as opposed to 38% in Thailand and 41% in Vietnam (United Nations Educational, Scientific and Cultural Organization, 2023). In a survey done by Meadley (2023)60% of students claimed to have never used an AI-powered learning tool, while only 25% of educators stated they were confident enough to use AI in their teaching. The most common reasons impeding AI development in Laos are (1) the absence of AI-related infrastructure, (2) under-skilled trainers, and (3) inadequate policy frameworks by the government. Most of Laos' education institutions do not have AI-based marketing systems, cloud services, reliable internet connectivity, and other educational resources (Asian Development Bank, 2021). There is also no training provided to tutors which hampers the utilization of AI tools in.

Table 1 Research Hypotheses

Hypothesis	Dependent Variable	Independent Variable	Expected Relationship	Supporting Literature	Description
H1	BI	ATB	+	Chai et al. (2021)	A student's positive attitude toward AI in education increases their intention to adopt AI tools for learning.
H2	BI	SN	+	Ajzen (1991)	Students are more likely to adopt AI if they perceive social pressure or encouragement from peers, faculty, or institutions.
H3	BI	PBC	+	Ivanov et al. (2024)	Students who feel confident in their ability to use AI tools are more likely to adopt them.
H4	BI	PA	+	Chai et al. (2021)	AI tools that align with existing teaching methods are more likely to be accepted by students.
H5	AU	BI	+	Davis (1985)	Students who intend to use AI for learning are more likely to integrate it into their academic activities.
H6	AU	PBC	+	Ajzen (1991)	Students who feel in control of using AI are more likely to engage with AI-based learning.
H7	ATB	PU	+	Davis (1985)	Students who perceive AI as applicable in their learning develop a positive attitude toward using it.
H8	ATB	PEOU	+	Davis (1985)	If AI tools are easy to use, students will have a more positive attitude toward adopting them.
H9	BI	AIL	+	Dwivedi et al. (2021)	Students with higher AI literacy are more likely to adopt AI in their education.
H10	BI	AC	+	Ibrahim et al. (2017)	Greater access to AI tools, stable internet, and technical support increases AI adoption in education.
H11	SN	ATB	+	Ajzen (1991)	If students see AI being widely accepted by their peers or teachers, they will develop a positive attitude toward using it.
H12	SN	PBC	+	Ajzen (1991)	Social influences can increase students' confidence in using AI effectively.
H13	BI	PU	+	Davis (1985)	If students perceive AI tools as applicable, they will be more likely to develop behavioral intentions to adopt them in their education.

Research Gap

There is considerable research on AI adoption in education, but these studies center on Western nations where the impact of AI integration faces significant challenges due to existing digital infrastructure, trained educators, and government policies fostering AI-centric education (Zhao et al., 2022). In comparison, countries like Laos struggle with underdeveloped infrastructure, scant pedagogical training, and low AI literacy rates among the student population, all of which greatly restrict the application of AI in higher education (United Nations Educational, Scientific and Cultural Organization, 2023). Though TAM and TPB have been cited extensively in technology adoption frameworks, these models do not include context-specific limitations such as AIL, PA, and AC (Du et al., 2024; Koch et al., 2024; Zhao et al., 2022). This absence of research combining resource-constrained environments with these three variables in AI adoption frameworks illustrates the gap in the literature. In addition, prior research on AI in education has concentrated mainly on the disciplines of engineering, computer science, and general business, insufficiently addressing marketing education's unique challenges, even as predictive analytics, automated digital marketing, and sentiment analysis are core competencies adapted to industry (Elhajjar et al., 2021). In Laos, only 12% of universities have infused AI into their programs, while the figures for Thailand and Vietnam are 38% and 41%, respectively, thus deepening the digital disparity. Furthermore, Meadley (2023) reports that 60% of students have never utilized AI-powered learning resources, and only 25% of the teaching staff express any readiness to use AI within their instruction. This research tackles these issues by applying the TAM and TPB in conjunction with AIL, PA, and AC approaches, thereby enriching the analysis of AI use in marketing education in Laos. By identifying key barriers and proposing policy recommendations, this research contributes to AI education strategies, faculty development programs, and institutional reforms to improve AI integration in marketing curricula in developing nations.

Methodology

The Research Context

This research utilizes a survey approach grounded within a quantitative research framework to analyze the factors affecting AI adoption in teaching marketing in Laos. Data was obtained at one specific time in the research study, applying a cross-sectional approach. The research incorporates SEM to analyze the relationships among several constructs. The rationale for using SEM is that it can evaluate intricate relationships among several latent variables while considering measurement error distortions.

The sample selected for the study is 165 marketing students from different universities in Laos. The sample's sufficiency for the SEM was evaluated considering the guidelines provided by Hair et al. (2014), which suggests a 5 to 10 respondents per estimated parameter ratio. Consequently, with the number of latent variables and the observed indicators available for the study, at least 150 responses were needed for statistical reliability. From these, 165 were chosen, which is statistically valid for SEM, meeting Hair et al. (2014) recommendations for path analysis and hypothesis testing (Kline, 2018). Additionally, these figures align with other studies regarding technological adoption in educational settings (Dwivedi et al., 2021). With these findings, the study can meaningfully add to the existing literature.

A more sophisticated capture of students' perceptions and attitudes around AI adoption was collected using a seven (7) point Likert scale (1 = Strongly Disagree to 7 = Strongly Agree). Survey pretesting was conducted on a small sample of students to determine if the survey was clear and coherent. In addition, an expert panel reviewed the items for content validity to ensure they corresponded to the study's theoretical framework.

The adopted survey was divided into three sections: (1)-Demographic Information, (2)-Constructs on the Adoption of AI, and (3)-Behavioral Intention and Actual Use of AI. All constructs with definition, sample items, and references can be found in Table 1. This alignment ensures that the measurement tool is designed on a sound theoretical framework while helping measure students' adoption of AI in marketing education.

Survey data were obtained by distributing questionnaires using Google Forms across several universities. An academic year stratified random sampling technique was applied as a first step in the selection process to capture representation from the first-year to the final-year students in the marketing course.

Data analysis

The steps performed in analyzing the data were sequential to ensure precision, trustworthiness, and credibility when measuring AI adoption in marketing education. First, the dataset was screened to confirm the absence of missing values, outliers, and normal distribution before proceeding with other statistical analyses. Missing values were handled using suitable imputation techniques. Outliers were determined using Z-scores (±3.29) and Mahalanobis distance ($p < 0.001$). Normality was assessed through skewness and kurtosis, and ensured that the values remained within the accepted range of ±2.0 (Byrne, 2012). For the assessment of internal consistency and reliability, Cronbach’s Alpha (α) was computed, with values above 0.70 deemed acceptable and values above 0.80 indicating good reliability (Hair et al., 2014). To strengthen the reliability assessment, the construct’s “Cronbach’s Alpha if Item Deleted” was evaluated to see whether item removal would significantly improve overall construct reliability. In the context of the study by Cronbach (1951) and Taber (2018), if the removal of an item in a single case increased Cronbach's Alpha, this indicated weak correlation with other items and required revision; if deletion turned out to decrease Alpha, the item was kept as it enhanced internal consistency. Each item of interest was screened, and descriptive statistics were calculated, including mean, standard deviation, skewness, and kurtosis to summarize the data distribution. Subsequently, the measurement model was tested to ensure the conceptual framework was sound by assessing reliability and validity. In particular, composite reliability, which had to be equal to or greater than 0.70 ($CR \geq 0.70$), was used for internal consistency, while AVE, which had to be equal to or greater than 50% ($AVE \geq 0.50$), was used for convergent validity (Fornell & Larcker, 1981). Discriminant validity was verified using the Fornell-Larcker criterion, ensuring that each construct was distinct from others and did not exhibit excessive correlation. These steps collectively ensured that the dataset was well-prepared for further inferential analysis and hypothesis testing.

Result

The demographics and behaviors of 165 marketing professionals regarding their usage of AI tools. Most respondents were women (70.9%), and most were in the 18-23 age group (96.4%). Most respondents appear to be novice marketers; 52.7% reported less than a year of experience, while 43% reported having 1 to 3 years of experience. The respondents widely use AI tools; 41.2% reported using them daily, and 38.8% reported using them at times. The respondents preferred learning online through tutorials (45.5%) or self-teaching with manuals (33.9%), leaving workshops and school programs less frequent. AI tools were mainly used for research and analysis (66.1%), followed by data visualization (23.6%), while content creation and other uses were far less common. The results indicate that younger, novice marketers may use AI for self-directed analytic tasks and learn from informal educational resources.

Table 2 Demographic and Behavioral Characteristics of Marketing Students in AI Adoption

Demographic Behavioral Factor	Category	Frequency	Percent
Gender	Male	48	29.10
	Female	117	70.90

Demographic Behavioral Factor	Category	Frequency	Percent
Age	Under 18	2	1.20
	18-20	80	48.50
	21-23	79	47.90
	24-26	2	1.20
	Above 26	2	1.20
Years of Experience in Marketing	Less than 1	87	52.70
	01-Mar	71	43.00
	04-Jun	3	1.80
	More than 6	4	2.40
Frequency of AI Tool Use	Daily	68	41.20
	Weekly	28	17.00
	Occasionally	64	38.80
	Rarely	5	3.00
Preferred Mode of Learning AI Tools	Online tutorials or courses	75	45.50
	Workshops or seminars	5	3.00
	Self-learning with manuals/guides	56	33.90
	Formal education programs	29	17.60
Primary Purpose of Using AI Tools	Research and Analysis	109	66.10
	Content creation	10	6.10
	Data visualization	39	23.60
	Other	7	4.20

The survey items have a set of descriptive statistics, which include the item’s minimum, maximum, mean, standard deviation, skewness, and kurtosis, which help in understanding the variability and distribution of the data (Hair et al., 2014). The mean values range between 4.42 and 5.42, indicating that the respondents moderately to highly rated all the constructs provided to them (Kline, 2018). The standard deviation measures suggested that respondents’ answers were moderately varied, with values between 1.558 and 1.854. All skewness values are negative and for all items fall between -1.177 and -0.331, suggesting that the distribution is a bit skewed toward the left, meaning that there were greater responses toward the higher side of the Likert scale (Tabachnick & Fidell, 2013). While the kurtosis values for all items range between -0.863 and 0.613, which puts them in the interval of ±2, shows that they are not excessively pointy or flat, suggesting relatively normal distribution (Byrne, 2012). The PU and BI items having the highest mean scores indicate that respondents strongly perceived AI tools to be useful and intended to adopt them (Davis, 1985). Meanwhile, the mean scores for PEU and PBC were somewhat lower, indicating difficulties regarding the usability of AI tools and the control one has over deciding to use AI.

For this study, we applied Cronbach’s alpha to measure the internal consistency of different constructs regarding the research use. This metric computes reliability by evaluating the interrelatedness of items within a given set. All the constructs within the scope of our analysis had Alpha values exceeding 0.98, which indicates a great degree of dependability. The high values indicate that the numerous items in the constructs reliably represent the same underlying idea. Extremely high alpha values should be interpreted cautiously because they may indicate problems with the constructs' differentiation. Thus, some items may be too similar to each other. Nonetheless, these results, as stated above, strongly suggest that the scales would require careful consideration to ensure an appropriately defined measurement of the constructs.

Table 3 Model Fit Summary for CFA

Indices	**Abbreviation**	**Recommended Threshold (Kline, 2018)**	**Model 1**	**Model 2**	**Model 3**
Chi-Square	χ^2	p > 0.05	136.598	112.426	751.426
Normed Chi-Square	χ^2/df	$1 < \chi^2/df < 5$	1.707	1.405	2.076
Normed Fit Index	NFI	> 0.90	0.954	0.963	0.981
Comparative Fit Index	CFI	> 0.90	0.980	0.989	0.934
Tucker-Lewis Index	TLI	> 0.90	0.974	0.985	0.920
Root Mean Square Error of Approximation	RMSEA	< 0.08 (good), < 0.05 (excellent)	0.660	0.050	0.080

In Table 3, the goodness-of-fit indices for absolute (chi-square & normed chi-square) and incremental fit (NFI, CFI, TLI), including RMSEA as an approximation error, are provided for Model 1, Model 2, and Model 3 alongside model acceptance thresholds for each fit. The indices evaluate the degree of association between each theoretical model and the actual data, with established thresholds indicating an acceptable fit.

The three measurement model tables together show a robust set of properties to evaluate technology adoption stemming from various theoretical perspectives. The findings of Table 4 reveal excellent reliability and validity for the traditional behavioral model, as greater than 0.85 loading cutoffs were achieved alongside Cronbach's alpha outputs above 0.90. Table 5 shows that the TAM model also has similar solid results, although with some increase in the variability of PEU loadings (0.805-0.934). The most complete integrated model is provided in Table 6. It improves upon the most comprehensive pre-existing integration by AI constructs while maintaining strong measurement properties throughout. Most models showed robust fine composite reliability (which exceeded 0.90 in most cases) and fulfillment of convergent validity requirements (which was below 0.70 for almost all constructs) with strongly significant factor loadings ($p < 0.001$). The outcomes point that the traditional TPB model, with TAM, does well individually, while the expanded model 3 is better in that it blends elements of behavioral approaches to examine AI adoption within a single coherent structure without losing measurement rigor.

Model 1: The Theory of Planned Behavior (TPB)

Table 4 Measurement Model Results for TPB

Factors	Items	β	Factor loading	S.E.	t-Value C.R.	SMC	AVE	CR	Cronbach's α
Attitude Toward Behavior (ATB)	ATB3	1.000	0.947***			0.897	0.845	0.942	0.941
	ATB2	0.983	0.924***	0.044	22.473	0.854			
	ATB1	1.013	0.885***	0.052	19.539	0.783			
Perceived Behavioral Control (PBC)	PBC1	1.000	0.889***			0.790	0.790	0.919	0.919
	PBC2	1.050	0.909***	0.061	17.246	0.826			
	PBC3	0.980	0.868***	0.062	15.687	0.753			
Subjective Norms (SN)	SN1	1.000	0.879***			0.773	0.805	0.925	0.924
	SN2	1.061	0.919***	0.061	17.315	0.845			
	SN3	1.093	0.894***	0.067	16.387	0.799			
Behavioral Intention (BI)	BI3	1.000	0.937***			0.878	0.877	0.955	0.956
	BI2	0.994	0.934***	0.043	22.974	0.872			
	BI1	1.054	0.939***	0.045	23.402	0.882			
Actual Use (AU)	AU3	1.000	0.928***			0.861	0.847	0.943	0.943
	AU2	1.003	0.939***	0.046	22.025	0.882			
	AU1	0.953	0.893***	0.050	19.029	0.797			

Model 2: The Technology Acceptance Model (TAM)

Table 5 Measurement Model Results for TAM

Factors	Items	β	Factor loading	S.E.	t-Value C.R.	SMC	AVE	CR	Cronbach's α
Behavioral Intention (BI)	BI3	1.000	0.917***			0.841	0.838	0.939	0.956
	BI2	0.992	0.911***	0.051	19.345	0.830			
	BI1	1.053	0.918***	0.053	19.769	0.843			
Actual Use (AU)	AU3	1.000	0.912***			0.832	0.819	0.931	0.943
	AU2	1.008	0.930***	0.052	19.485	0.865			
	AU1	0.954	0.872***	0.057	16.813	0.760			
Attitude Toward Behavior (ATB)	ATB1	1.000	0.852***			0.726	0.787	0.917	0.941

Factors	Items	β	Factor loading	S.E.	t-Value C.R.	SMC	AVE	CR	Cronbach's α
	ATB2	0.965	0.896***	0.063	15.320	0.803			
	ATB3	0.971	0.912***	0.061	15.797	0.832			
Perceived Ease of Use (PEU)	PEU1	1.000	0.805***			0.648	0.723	0.886	0.881
	PEU2	1.218	0.934***	0.090	13.459	0.872			
	PEU3	1.137	0.805***	0.098	11.565	0.648			
Perceived Usefulness (PU)	PU1	1.000	0.872***			0.760	0.823	0.933	0.931
	PU2	1.095	0.962***	0.059	18.511	0.925			
	PU3	1.013	0.885***	0.063	16.032	0.783			

Examination of the map points to the strong interactions between PEU, PU, ATB, BI, and AU, which can help shed light on the role of AI in marketing education in Laos. ATB being strongly influenced by PEU (0.643) and PU (0.550) shows the need to have effective and user-friendly systems of AI that encourage positive users' propensity, which is in line with previous studies (Davis, 1985; Masrom, 2007). The strong influences of ATB on BI (0.683) and BI on AU (0.816) suggest that there are positive attitudes and intentions towards the actual use of AI (Ajzen, 1991; Scherer et al., 2019). Although there are issues with infrastructure and access in Laos, the user-friendly and practical importance of AI tools is likely to increase the rates for these activities. This data underlines the importance of significant targeted interventions focused on educational programs for improving AI literacy, enhancing user motivation, and demonstrating the power that AI can have in marketing education (Chai et al., 2021; Ivanov et al., 2024). These findings suggest that concentrating on user-friendly AI tools while simultaneously removing barriers to using them will improve the integration of AI into marketing education in Laos.

Integrating TPB, TAM, and Contextual Factors: The Foundation of Model 3

Table 6 Measurement Model Results for Model 3

Factors	Items	β	Factor loading	S.E.	t-Value C.R.	SMC	AVE	CR	Cronbach's α
Perceived Ease of Use (PEU)	PEU3	1.000	0.805***			0.648	0.722	0.886	0.881
	PEU2	1.069	0.932***	0.079	13.489	0.869			
	PEU1	0.881	0.806***	0.076	11.597	0.650			
Perceived Usefulness (PU)	PU3	1.000	0.887***			0.787	0.822	0.933	0.931
	PU2	1.075	0.958***	0.056	19.317	0.918			
	PU1	0.986	0.873***	0.061	16.113	0.762			
AI Literacy (AIL)	AIL3	1.000	0.853***			0.728	0.789	0.918	0.917
	AIL2	1.147	0.905***	0.076	15.068	0.819			

Factors	Items	β	Factor loading	S.E.	t-Value C.R.	SMC	AVE	CR	Cronbach's α
	AIL1	1.090	0.906***	0.072	15.086	0.821			
Pedagogical Alignment (PA)	PA3	1.000	0.931***			0.867	0.821	0.932	0.932
	PA2	0.992	0.887***	0.056	17.724	0.787			
	PA1	1.005	0.900***	0.055	18.311	0.810			
Accessibility (AC)	AC3	1.000	0.815***			0.664	0.763	0.906	0.904
	AC2	1.070	0.910***	0.078	13.687	0.828			
	AC1	1.090	0.892***	0.081	13.454	0.796			
Attitude Toward Behavior (ATB)	ATB3	1.000	0.897***			0.805	0.778	0.913	0.941
	ATB2	1.007	0.897***	0.060	16.922	0.805			
	ATB1	1.043	0.851***	0.069	15.207	0.724			
Subjective Norms (SN)	SN3	1.000	0.830***			0.689	0.702	0.876	0.924
	SN2	0.970	0.864***	0.076	12.702	0.746			
	SN1	0.923	0.819***	0.078	11.912	0.671			
Perceived Behavioral Control (PBC)	PBC3	1.000	0.867***			0.752	0.792	0.919	0.919
	PBC2	1.071	0.908***	0.068	15.750	0.824			
	PBC1	1.027	0.894***	0.067	15.393	0.799			
Behavioral Intention (BI)	BI1	1.000	0.875***			0.766	0.753	0.901	0.956
	BI2	0.939	0.858***	0.066	14.272	0.736			
	BI3	0.948	0.870***	0.065	14.588	0.757			
Actual Use (AU)	AU1	1.000	0.819***			0.671	0.741	0.895	0.943
	AU2	1.052	0.892***	0.079	13.261	0.796			
	AU3	1.046	0.869***	0.081	12.904	0.755			

The research indicates that focusing on user-friendly and practical applications of AI could increase acceptance within Laos, where digital literacy and resources are significantly deficient. To resolve these obstacles, it is important to design educational interventions to increase AI literacy and alleviate user apprehensions. Laos might be able to accelerate the adoption of marketing AI in education by launching programs focusing on the AI's unprecedented ability to transform marketing (Chai et al., 2021; Ivanov et al., 2024). By taking a user-driven approach and allowing reasonable access to AI, Laos can meet its challenges and promote innovation in AI for marketing education.

Model 3 is a fully articulated model encompassing the TPB, TAM, and contextual components, as well as additional aspects that aid in understanding AI adoption through the lens of marketing education. The TPB framework (Ajzen, 1991) focuses on ATB, SN, and PBC relations and how they interact with BI and AU. TPB provides a picture of sociocultural and psychosocial aspects that govern the adoption process, which includes social PBC. The TAM, developed Davis (1985), modifies the TPB by emphasizing PEU and PU as leading predictors of intention. These models put together are particularly useful in analyzing the intra- and inter-structural factors influencing the adoption of AI. Addressing the obstacles with AI adoption, such as lacking technical skills, academic mismatch, and resources of Governance Studies, Model 3 combines contextual factors like AIL, PA, and AC (Du et al., 2024; Koch et al., 2024; Zhao et al., 2022).

This framework provides a unique view on AI adoption by simultaneously employing the constructs of TAM and TPB along with contextual variables. The components of TAM-PU and PEOU determine ATB, which impacts BI and AU as delineated in TPB (Ajzen, 1991; Davis, 1985; Masrom, 2007). PBC, in turn, reinforces BI and AU by strengthening perceptions of one’s ability to overcome obstacles in challenging environments such as Laos (Fathema et al., 2015; Mohr & Kühl, 2021). Along with behavioral aspects, contextual factors also enhance the elements of the model's use by providing structural components. As for AIL, it boosts the understanding and confidence in AI, while PA ensures that the AI-powered tools can fulfill the targets of the curriculum, and AC enables the enhancement of resource and infrastructural access to AI (Bosnjak et al., 2020; Chahal & Rani, 2022). Model 3's integrated approach meets the specific barriers and pivots of AI adoption in Laos marketing education, offering pragmatic and precise advice.

Some bridging relationships between several important constructs were identified based on the estimates of regression weight and standardization for the model. The estimates of ATB, PEU, and PU all proved to be highly significant as their critical ratios (C.R.) and p-values were beyond the threshold (***$p < 0.001$). For instance, the regression weight of ATB on PEU is 0.526 with a critical ratio of 9.686, which indicates that PEU determines ATB to a considerable degree. To put it another way, the ratio indicates that PEU strongly influences the ATB. PU considerably influences ATB (0.471, C.R. = 9.959). This further supports that the respondents’ perception of the ease and usefulness of AI technologies affects their attitudes towards AI technology. In addition, AIL (0.196), PA (0.189), and AC (0.337) have positive effects on BI, which indicates that the more AI tools are integrated into the curriculum and made readily available, the more acceptance they gain. SN also demonstrates a strong positive influence on ATB (0.645) and PBC (0.353), suggesting that social perception and perceived control are relevant parameters for attitude and behavioral intention. The standardized regression effects are significant, all of which exceeded 0.5, indicating that these relationships are deep-rooted.

Table 7 Hypothesis Testing Results

Hypothesis	Model 1	Model 2	Model 3	Result
ATB <= PU	0.550 (0.054)***		0.575 (0.048)***	Support
ATB <= PEOU	0.628 (0.069)***		0.640 (0.055)***	Support
BI <= PU	0.199 (0.058)***		0.267 (0.053)***	Support
BI <= ATB	0.683 (0.076)***	0.502 (0.109)***	0.305 (0.095)***	Support
AU <= BI	0.816 (0.072)***	0.616 (0.098)***	0.623 (0.086)***	Support

Hypothesis	Model 1	Model 2	Model 3	Result
BI <= SN		0.118 (0.109)	-0.075 (0.101)	Not Support
BI <= PBC		0.296 (0.104)***	0.186 (0.059)**	Support
AU <= PBC		0.284 (0.096)***	0.279 (0.051)***	Support
BI <= PA			0.211 (0.042)***	Support
BI <= AIL			0.230 (0.049)***	Support
BI <= AC			0.456 (0.050)***	Support
SN <= ATB			0.644 (0.070)***	Support
SN <= PBC			0.453 (0.055)***	Support

Note: ***$p < 0.001$, **$p < 0.05$

Table 7 contains detailed results for structural equation modeling for the three frameworks of AI adoption at once, capturing both general tendencies and the Laos-specific adoption patterns. Observed core value technology acceptance influences had PU (β = 0.550-0.575, $p < 0.001$) and PEU (β = 0.628-0.640, $p < 0.001$), which dominate attitude formation regarding AI across the globe, and in particular, for Laos, where digital literacy is unevenly spread. Also, the Attitude-Behavior Intention relationship (β = 0.305-0.683, $p < 0.001$) granting was positive confirms that positive perceptions are satisfactorily associated with intention to adopt, although Lao users appear to depend more on personal capability beliefs (PBC: β = 0.186-0.296, $p < 0.01$) than social ones, as suggested by the non-significant Subjective Norms effect. Such a finding is unique in that it hints that Lao professionals tend to make technology choice decisions based on practical value rather than peer pressure. The lessons gotten to adjust model 3 were more extensive than previously: for educational purposes, Pedagogical Alignment (β = 0.211, $p < 0.001$) was found to be highly important, AI Literacy (β = 0.230, $p < 0.001$) for addressing gaps in existing skills, while Accessibility (β = 0.456, $p < 0.001$) for low level of infrastructural development parts was particularly noteworthy. This last factor had a powerful influence owing to Laos' limited connectivity. The sustained relevance of Behavioral Intention on Actual Use (β = 0.616-0.816, $p < 0.001$) along with the direct PBC impact (β = 0.279-0.284, $p < 0.001$) underscores that, motivation aside, actual engagement in Laos still requires a pathway to unlocking resource challenges. Collectively, these findings suggest that while broad frameworks for adoption are relevant, the effective integration of AI in Laos is pragmatically focused through the lens of tailored emphasis on: (1) demonstrating immediate impactful relevance, (2) user-friendly interface design that considers all skill levels, (3) training program localization, and (4) alleviation of physical accessibility barriers, with lesser social appeal stratagems in stark contrast to other cultures.

Conclusion and Discussion

AI adoption in marketing education in Laos, as shown in the current research, is deeply influenced by behavioral, structural, and contextual elements. With limited resources, AIL, PA, and AC, combined with TAM and TPB, form a strong model to understand AI adoption Scherer et al. (2019). These results corroborate prior research claiming that PEU and PU are prominent determinants in adopting technology (Davis, 1985; Granić & Marangunić, 2019). Particular to this study, the impact of PEU (0.526) and PU (0.471) on ATB suggests that Lao marketing students seek to have a more favorable view of AI as its functions become more self-evident and offer benefits towards their learning and career development. Positive perceptions begin with the ease of use of AI through its student-friendly design and functionality. Using AI tools increases students' perception of their value and diminishes resistance to its use. The benefits AI can provide through its uses in academics and professionalism enable students to put their theoretical learning into practice, which furthers PEU. AI system designs need to be user-centered to meet professional and academic requirements and aid Lao marketing students in overcoming infrastructural and digital literacy constraints. In order to help reshape the marketing teaching and learning process in Laos, all AI tools must be created with particular emphasis on ease of use, as well as demonstrated effectiveness

Laos has difficulties incorporating AI in marketing education because of inadequate infrastructure and low digital literacy, which is common in developing countries. Similar obstacles were encountered by Mohr & Kühl (2021) who noted that the PBC resource deficits and placement external constraints are pivotal for enhancing PBC. This suggests that PBC is important in students' intention and AUs of AI tools, emphasizing the need for students to be provided with the necessary confidence, resources, and skills. Evidence suggests that improved PBC means that both aid the development of technical skills and foster an environment where students are confident using AI with external challenges. Chai et al. (2021) eloquently put it when arguing that self-efficacy, coupled with specific technical training, is essential for actualizing intentions toward adopting AI technology. Various AIL, PA, and AC point to the fact that comprehensive policies and frameworks need to be in place for AI adoption. Providing a better understanding of AI helps eliminate fear, and the foundations of knowledge get students interested in AI. These tools focus on learners' academic and career goals, further aiding in minimizing barriers. Putting in place necessary resources and infrastructure enables all students and learners to utilize AI technology, thereby addressing the systemic inequities in access to AI. This substantiates the findings of Ivanov et al. (2024) which states that the adoption of AI significantly increases when AI is aligned with the curriculum objectives and when resources are made more accessible. To bridge the existing gaps, Laos has to incorporate a wide range of strategies, such as building a stronger digital infrastructure, providing AI resources, and improving AI literacy among educators and learners. Such reforms are critical to ensure that learners understand the importance of AI and how to utilize it proficiently in their marketing studies.

The limited effect of SN on BI (0.122) suggests that sociocultural and organizational factors are not critical for AI adoption in Laos. This is consistent with Ajzen (1991) who stated that the role of SN varies within and between cultures. In developing countries like Laos, which do not have institutional and peer support structures for AI, the effectiveness of SN could be low. BI's strong positive relations with ATB (0.491) also signify the need to build favorable AI attitudes. These results are in agreement with Scherer et al. (2019) and others that found ATB to be a determinant in teachers' intended uses of technologies. The important impact of AC on BI and AU suggests that infrastructure and resources are critical. The problems that many developing countries face in providing the infrastructure and resources needed to implement AI, as discussed by Demas et al. (2018) is justifiable. The best use of AI, whether in PA or not, raised the issue of educational purpose as the framework within which systems will be designed, Fathema et al. (2015) and Chahal & Rani (2022) would endorse.

The previous paragraph implies that the challenges AI and marketing education pose in Laos are under-researched and therefore need more focused AI marketing education research in developing countries. While the existing literature focuses on AI exploitation in education, it primarily centers around developed countries. Unlike them, this academic research shifts the puzzle to the resource-deficient context, paying attention to behavioral, structural, and contextual determinants of AI exploitation. This research fills the literature gap where there is a combination of the TPB, TAM, and proprietary models, but without attention to the developing countries' context. Furthermore, the research employs AIL, PA, and AC as context-adjustable variables of the previously mentioned frameworks. That leads to more accurate information about AI adoption in the modeling frameworks addressing understudied dimensions of the adoption phenomenon.

The research fills the gap of limited available literature on the behavioral aspects of PEU, PU, and PBC and their structural constraints in Laos. It considers the importance of using tailor-made initiatives such as user-friendly AI applications, targeted technical training, and curriculum integration to foster a positive attitude and intention towards adoption. In addition, this study provides context and infers that the variable PBC has direct bearings not only on behavioral intentions but also on the actual usage of these constructs, which aids in the understanding that the impact of infrastructure and accessibility goes beyond the theoretical framework. These barriers and enablers provide a vital perspective to the global discourse on fair and equitable AI adoption within underdeveloped regions. This study finally validates the application of the theoretical models in practice. It suggests that further investigation needs to be conducted on how these models can serve as a basis in policy frameworks to improve AI education systems.

The study results show that adopting AI in marketing education in Laos is affected by a combination of behavioral, structural, and contextual factors. PEU, PU, and PBC are crucial in shaping how students perceive, intend to use, and engage with AI tools. The study emphasizes the importance of PEU and PU in shaping positive perceptions towards AI, as students willingly adopt technologies with user-friendly interfaces and offer clear academic/professional value. This demonstrates the need to design AI tools that are easy to use and useful for students' academic and professional goals. Moreover, this study indicates that PBC is critical in determining BI and AU. Providing adequate training and materials makes students more confident, positively affecting AI technology adoption. Students' learning with AI is influenced by AIL, PA, and AC, where those who consider AI to be available and relevant to their activities are willing to use it. However, the weaker influence of SN on the adoption in Laos indicates that more support from institutions and colleagues is needed, since social and institutional pressures appear to be weak. This study concludes that to integrate AI effectively in Lao marketing education, it is necessary to provide more than just AI tools; the tools also need to be efficient, proper training should be given, and the infrastructure should be improved.

Limitations and Future Research

This study, AI and Challenges of Marketing Education Among Students in Laos, has gaps that indicate particularly interesting future studies. This focus on marketing students in higher education tends to ignore non-related professional and academic disciplines, indicating the necessity of further studies encompassing broader demographics. Such a cross-sectional design only captures one point, showing the gap in longitudinal studies that measure AI adoption. Moreover, self-reported data can be misleading and biased. Therefore, future analysis should include objective measures such as monitoring AI tool usage. As the scope of this study was limited to Laos, there is a possibility that the results are not valid in other regions; more comparative cultural and technological studies would be more beneficial. Lastly, a limitation of this study is its lack of focus on external factors such as government policies, industry partnerships, and economic conditions; the' impact of these policies on AI adoption in education could be investigated further. By focusing on these gaps, more practical and sound approaches can be developed to ease the integration of AI within education, where resources are mainly constrained.

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Data Availability Statement: The raw data supporting the conclusions of this article will be made available by the authors, without undue reservation.

Conflicts of Interest: The authors declare that the research was conducted without any commercial or financial relationships that could be construed as a potential conflict of interest.

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