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Preparing TVET Students for the AI Era: Effects of AI-Integrated Courses on Academic Performance and Career Adaptation through Student Engagement and Competency

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ABSTRACT

This study explored the effects of AI-integrated courses on academic performance and career adaptation among TVET students, with student engagement and student competency as key mediating variables. Research exploring how AI-integrated courses simultaneously influence both academic and career outcomes in the TVET context is still limited, despite increased interest in AI adoption in education. Based on Social Cognitive Theory, Self-Determination Theory, and Career Construction Theory, this study proposes an integrated conceptual model to explain how AI integration may shape student learning and career readiness in the AI era. A quantitative research approach was used, and survey data from 765 TVET students were analyzed using IBM SPSS Statistics 26 for descriptive statistics and SmartPLS 4 for path and mediation analyses. The results showed that AI-integrated courses did not have a significant direct effect on academic performance or career adaptation but significantly enhanced student engagement and student competency. Student engagement emerged as the strongest predictor of both academic performance and career adaptation, while student competency significantly influenced academic performance only. Additionally, mediation analysis showed that student engagement fully mediated the relationships between AI-integrated courses and both outcomes, whereas student competency partially mediated only the relationship with academic performance. The model exhibited moderate explanatory power and acceptable predictive relevance across key outcomes. Overall, the findings suggest that the effectiveness of AI-integrated courses depends more on fostering active student engagement than on technology alone. This study contributes to the literature by providing an integrated framework for understanding AI adoption in TVET and offering practical implications for designing engaging and competency-driven learning environments to enhance student success in the AI era.

Keywords: AI-integrated courses in TVET, student engagement, student competency, academic performance, career adaptation

INTRODUCTION

Artificial intelligence (AI) has become increasingly adopted across various sectors, including education, moving beyond experimental applications to serve as an automated, real-time assistant supporting administrative tasks, instructional delivery, and student learning (Sajja et al., 2026). Given the increasing potential of AI technologies in education—including the enhancement of teaching effectiveness, personalization of instruction, improvement of academic performance and engagement, and development of skills aligned with evolving labor market demands—educational institutions worldwide are increasingly interested in integrating AI into teaching and learning processes for both teachers and students (Asad & Anwar, 2025; Vieriu & Petrea, 2025).

Recent studies have shown that the integration of AI into higher education courses can directly improve academic performance. AI-driven solutions that offer individualized learning experiences, real-time feedback, and adaptive learning pathways may enhance students' academic performance, motivation, and engagement (Merino-Campos, 2025). Furthermore, AI-integrated courses are associated with improved career adaptation by enabling students to develop AI literacy, technical competencies, and the ability to work effectively alongside AI technologies in rapidly evolving labor markets (Ejjami, 2024).

While AI integration in education and vocational training has become increasingly important for enhancing students' academic performance and career readiness, the effectiveness of AI-driven teaching and learning largely depends on students' ability to actively engage in learning and competently utilize AI tools (Vieriu & Petrea, 2025). Student engagement can promote stronger academic performance and support students' adaptation to the changing demands of the labor market (Jiang et al., 2024). Similarly, student competency—including academic capability, career-related skills, and adaptability—plays a crucial role in shaping both academic success and career adaptation (Akkermans et al., 2018). According to Zary and Zary (2025), students in higher education generally demonstrate stronger AI literacy, engagement, and competency than students in Technical and Vocational Education and Training (TVET), partly due to differences in educational approaches, resource availability, and curriculum design. Moreover, the integration of AI into TVET remains limited compared to its adoption in general higher education (Kimutai et al., 2025).

In the Cambodian context, AI adoption in TVET remains at an early stage, despite increasing national attention to digital transformation and workforce modernization. Cambodian TVET institutions are under growing pressure to prepare students for AI-enabled industries; however, many institutions continue to face challenges such as limited technological infrastructure, insufficient AI-related curriculum integration, and unequal access to digital learning resources. These constraints may hinder students' opportunities to develop AI literacy, actively engage in AI-supported learning, and build the competencies required for future employability. As Cambodia seeks to strengthen its skilled workforce to remain competitive in the regional and global labor markets, understanding how AI-integrated courses can enhance TVET students' academic and career outcomes has become particularly important.

In addition, TVET students often encounter unique challenges compared to general higher education students, including limited exposure to AI technologies, limited experience in using AI tools for learning, and weaker readiness to adapt to technology-driven workplace changes. These challenges make student engagement and student competency especially important mechanisms in AI-supported TVET education. While student competency refers to students' capacity to apply pertinent technical and adaptive skills, critically evaluate AI-generated information, and use AI technologies effectively, student engagement reflects students' active participation, motivation, and commitment to learning. Together, these factors may explain how AI-integrated courses translate into meaningful academic performance and career adaptation outcomes.

Although prior studies have examined the effects of AI on academic performance, student engagement, student competency, and career adaptation, most have focused on higher education settings and investigated these relationships separately. Limited research has explored how AI-integrated courses simultaneously influence both academic performance and career adaptation in TVET, particularly through the mediating roles of student engagement and competency. This gap is especially significant in the Cambodian TVET context, where AI integration is still emerging and where students face distinct educational and workforce preparation challenges. By focusing on Cambodian TVET students, this study extends existing AI in education research beyond general higher education and provides context-specific insights into how AI-supported learning can enhance both academic and career-related outcomes.

Thus, this study aims to address this gap by examining the effects of AI-integrated courses on academic performance and career adaptation among Cambodian TVET students, with particular attention to the mediating roles of student engagement and student competency. Through this integrated approach, the study advances understanding of how AI can be effectively leveraged to prepare TVET students for success in the AI era.

LITERATURE REVIEW

AI-Integrated Courses in TVET

AI-integrated courses in TVET refer to training programs that incorporate artificial intelligence technologies into the teaching and learning processes to enhance instructional delivery, skill development, and student learning outcomes. In this study, AI integration includes multiple forms of educational AI use, such as AI-powered learning support tools (e.g., generative AI assistants and chatbots), intelligent tutoring systems, automated feedback and assessment tools, simulation-based training platforms, and AI-related curriculum content designed to improve students' AI literacy and technical readiness (Southworth et al., 2023). AI is increasingly used in higher education to support individualized learning, research activities, and academic problem-solving (Merino-Campos, 2025; Vieriu & Petrea, 2025). Khairuddin et al. (2024) found that students have favorable opinions about using AI, particularly for brainstorming, simplifying complex information, and enhancing research understanding. Consequently, many higher education institutions have adopted AI not only for teaching and learning but also for administrative efficiency (Ajani et al., 2025).

In TVET, adoption of AI has drawn more attention due to its ability to improve the development of practical skills, provide step-by-step procedural guidance, and deliver immediate corrective feedback during technical training (Zary & Zary, 2025). Unlike general higher education, AI integration in TVET often emphasizes hands-on applications, simulation-based skill training, and workplace-oriented problem solving, making the learning context more practice-driven and employment-focused (Leong, 2025). Studies suggest that AI-integrated TVET programs can improve training effectiveness by enabling personalized learning pathways and adaptive instructional support (X. Lin et al., 2025).

However, prior research has yielded conflicting results regarding the effects of AI integration. While some studies indicate that AI directly improves academic achievement and learning efficiency (Younas et al., 2025), others suggest that students' active use of AI technologies and their ability to use them effectively are key factors in determining the extent to which AI is beneficial (Alexis & Pavlatou, 2026). This inconsistency suggests that AI may not directly influence student outcomes but may instead operate through critical learner-related mechanisms, particularly student engagement and competency. Although prior research has separately examined AI's effects on academic performance or employability, few studies have investigated a comprehensive integrated model linking AI-integrated courses with both academic performance and career adaptation through mediating variables, especially in TVET contexts.

Student Engagement

Student engagement refers to the extent to which students actively, cognitively, and emotionally students participate in learning activities (Alamsyah et al., 2024). It is frequently understood as a multidimensional construct that includes behavioral engagement (effort and involvement), cognitive engagement (critical thinking and deep learning), and emotional engagement (interest, motivation, and positive attitudes) (Fredricks et al., 2004).

Previous studies consistently show that highly engaged students typically perform better academically (Çali et al., 2024; Sahito et al., 2025). Furthermore, active engagement supports students' adaptability to evolving career demands by developing persistence, self-regulation, and professional confidence (Oliveira & Marques, 2024). Student engagement is particularly relevant in AI-integrated learning environments, where AI technologies provide interactive feedback, adaptive instruction, and personalized learning experiences (Vieriu & Petrea, 2025). Chatbots, intelligent tutoring systems, and simulation-based learning tools are examples of AI-driven platforms that can improve cognitive processing, boost emotional motivation, and encourage behavioral engagement (Fortuna et al., 2025). However, findings remain inconsistent regarding whether AI itself increases engagement or whether students' existing motivation determines the effectiveness of AI-supported learning (Kovari, 2025).

These conflicting results suggest that one important mediating mechanism through which AI-integrated courses affect academic and career outcomes is student engagement. Despite its significance, the mediating role of engagement in understanding how AI integration affects both academic performance and career adaptation simultaneously, especially among TVET students, has received little attention.

Student Competency

Student competency refers to students' abilities, knowledge, and skills required to perform academic and practical tasks effectively (Wong, 2020). Student competency in this study mainly focuses on AI literacy and technical competence in the context of AI-integrated learning, including the capacity to use AI tools effectively, critically assess information generated by AI, solve problems with AI support, and understand ethical issues surrounding AI use (Feng & Carolus, 2026).

In general, competent students perform better academically and have better employability prospects (Zakir et al., 2025). Kenayathulla et al. (2019) argued that students equipped with both technical and transferable competencies are more likely to sustain long-term career success. However, AI integration can also create challenges when students lack sufficient digital or AI-related competencies (Zhou & Peng, 2025). Institutions increasingly recognize the need to develop students' AI capabilities to ensure effective AI adoption and maximize learning benefits (Southworth et al., 2023).

Although previous studies have separately linked competency with AI integration, academic achievement, and career outcomes, there remains limited evidence on whether competency serves as an explanatory pathway through which AI-integrated courses influence both academic performance and career adaptation. To address this gap, this study looks at student competency as a mediator in an integrated framework.

Academic Performance

Academic performance is anticipated learning outcomes (Steinmayr et al., 2014). Instead of using objective institutional grade records, this study measures academic performance using students' self-reported evaluations of their grades, learning achievement, academic satisfaction, and achievement of academic goals.

Academic performance is influenced by institutional, individual, and environmental elements (Brew et al., 2021; Suleiman et al., 2024; Wang & Chen, 2024). AI-integrated courses have been identified as one important institutional factor, as AI-supported learning environments may improve understanding, efficiency, and academic productivity (H. Lin & Chen, 2024).

Evidence suggests that institutions adopting AI in teaching often report better student outcomes and improved completion rates (Younas et al., 2025). Similarly, higher academic outcomes are typically attained by students who are more proficient with AI technologies (Singh et al., 2025). Student engagement also plays a crucial role, as active behavioral, cognitive, and emotional participation significantly contributes to academic success (Yaseen et al., 2025). However, earlier research has concentrated on conventional higher education rather than TVET settings, where academic performance may require mastery of both theoretical knowledge and practical skills. By examining academic achievement in AI-integrated TVET education through both engagement and competency mechanisms, this study expands on previous research.

Career Adaptation

Career adaptation, according to Career Construction Theory, is an individual's ability and resources to deal with shifting career demands, transitions, and obstacles at work (Savickas, 2013). Concern, control, curiosity, and confidence are typical components of career adaptation, all of which assist people in navigating unstable labor market conditions and changing occupational needs.

For TVET students, career adaptation is particularly important because vocational education is linked to immediate employability and workforce readiness. Previous studies show that engaged and competent students are better able to adapt to career changes and sustain employability over time (Poláková et al., 2023). TVET students who actively participate in practical training and develop relevant competencies are more likely to transition successfully into employment (Zixuan et al., 2025). AI-integrated training programs may further enhance career adaptation by exposing students to emerging workplace technologies and improving digital readiness (Leong, 2025).

However, existing research has examined traditional determinants of career adaptation, such as motivation and competencies, with limited attention to how AI-integrated learning environments may shape students' adaptive career readiness. Moreover, the relationship between AI-integrated courses, engagement, competency, and career adaptation has rarely been examined simultaneously in one comprehensive model. This study addresses this gap by examining how AI-integrated courses affect career adaptation through student engagement and competency.

THEORETICAL AND CONCEPTUAL FRAMEWORKS

Three complementary theories serve as the theoretical foundation for this study: Social Cognitive Theory (SCT), Self-Determination Theory (SDT), and Career Construction Theory (CCT). Together, these theories offer a thorough explanation of how AI-integrated courses affect TVET students' academic performance and career adaptation through student engagement and competency.

Social Cognitive Theory

The Social Cognitive Theory (Bandura, 1986) emphasizes the reciprocal interaction among environmental factors, personal factors, and behaviors. According to SCT, learning occurs through continuous interactions between individuals and their environments, where external conditions can shape individuals' beliefs, competencies, and actions.

In this study, AI-integrated courses represent the environmental factor that provides students with AI-supported learning experiences, including intelligent feedback, personalized learning support, and interactive problem-solving opportunities. Students' self-efficacy, or their confidence in their capacity to use AI tools and complete academic work successfully, can be improved by these learning environments. Higher self-efficacy can strengthen students' confidence in using AI technologies, thereby improving their student competency, particularly AI literacy, technical skills, and critical evaluation of AI-generated information.

Furthermore, SCT explains that environmental support can influence students' learning behaviors, suggesting that AI-integrated courses may also encourage greater student engagement through reciprocal learning interactions, active experimentation, and continuous feedback. Therefore, the theoretical foundations for the relationships between AI-integrated courses and both student engagement and student competency are provided by SCT.

Self-Determination Theory

The Self-Determination Theory (Ryan & Deci, 2000) explains how learning practices and performance results are influenced by motivation. According to SDT, when three fundamental psychological needs are met—autonomy (feeling in charge of learning), competence (feeling capable of mastering tasks), and relatedness (feeling connected to the learning environment)—people are more likely to participate actively and perform well.

In this study, while student competency reflects students' perceived ability and confidence in applying AI-related information and skills, student engagement measures students' behavioral, cognitive, and emotional participation in learning. AI-integrated courses can foster relatedness through interactive learning experiences, competence through instant feedback and skill development, and autonomy through tailored learning pathways.

When these psychological requirements are met, students are more inclined to engage fully, persevere through difficult assignments, and build stronger skills, all of which improve their academic performance. Student engagement is expected to directly improve academic outcomes and strengthen students' readiness to adapt to future career demands. Similarly, student competency can improve academic achievement by enabling effective task performance and independent problem-solving. Hence, the relationships between student engagement and academic performance, student engagement and career adaptation, student competency and academic performance, and student competency and career adaptation are supported by SDT.

Career Construction Theory

The Career Construction Theory (Savickas, 2005, 2013) explains how individuals develop adaptive resources to manage career-related tasks, transitions, and uncertainties. According to CCT, career concern (planning for the future), career control (taking responsibility), career curiosity (exploring opportunities), and career confidence (believing in one's ability to succeed) are the four main dimensions of career adaptation, which describe an individual's readiness and capacity to deal with changing career environments.

Student engagement and competency, in this study, are considered important adaptive resources that prepare TVET students for future career challenges in an AI-driven labor market. Students who are engaged are more likely to investigate job options, stay motivated to develop their skills, and exhibit proactive career planning. Similarly, competent students who possess AI literacy and technical capabilities are better prepared to adapt to technological changes and evolving job requirements.

AI-integrated courses may indirectly strengthen students' career adaptability by fostering active engagement and building competencies necessary for future employability. Therefore, CCT provides theoretical justification for understanding how student engagement and student competency contribute to career adaptation.

Integrated Theoretical Framework and Conceptual Model

The suggested relationships in this study are coherently explained by the integration of SCT, SDT, and CCT. First, Social Cognitive Theory explains how AI-integrated courses as environmental learning conditions influence student engagement and student competency. Second, Self-Determination Theory explains how student engagement and competency function as motivational and capability-related mechanisms that enhance academic performance. Third, Career Construction Theory explains how these same mechanisms contribute to students' readiness to adapt to future career challenges. Collectively, these theories support the study's direct and indirect pathways, especially the mediating functions of student engagement and student competency in linking AI-integrated courses to academic performance and career adaptation. **Figure 1** presents the study's conceptual model based on the preceding theoretical foundations.

Research Questions

The research questions of the study are as follows:

- What are TVET students' perceptions of AI-integrated courses, engagement, competency, academic performance, and career adaptation in the AI era?
- How do AI-integrated courses affect TVET students' academic performance and career adaptation, both directly and indirectly, through student engagement and student competency?
- To what extent do student engagement and student competency predict academic performance and career adaptation among TVET students?

Hypotheses

Hypothesis 1: AI-integrated courses significantly influence:

H1a: Academic performance

H1b: Career adaptation

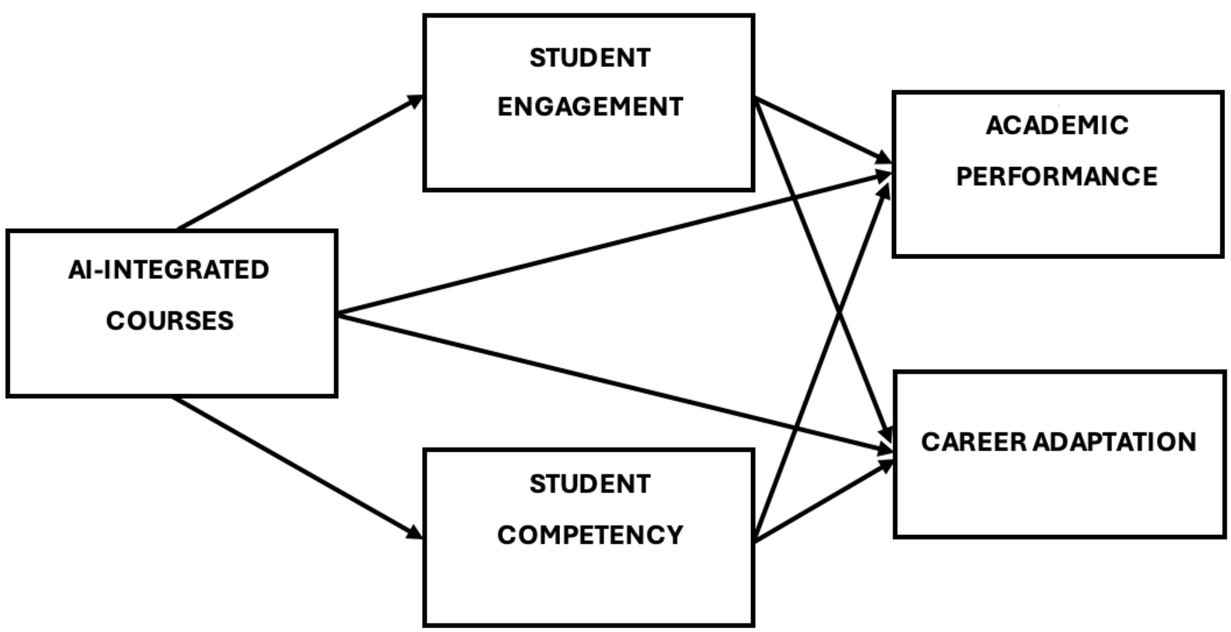

Figure 1. Conceptual Model (Source: The author)

H1c: Student engagement

H1d: Student competency

Hypothesis 2: Student engagement significantly influences:

H2a: Academic performance

H2b: Career adaptation

Hypothesis 3: Student competency significantly influences:

H3a: Academic performance

H3b: Career adaptation

Hypothesis 4: Student engagement mediates the relationships between:

H4a: AI-integrated courses and academic performance

H4b: AI-integrated courses and career adaptation

Hypothesis 5: Student competency mediates the relationships between:

H5a: AI-integrated courses and academic performance

H5b: AI-integrated courses and career adaptation

METHODOLOGY

Research Design

This study employed a quantitative research methodology using structural equation modelling (SEM) to investigate the effects of AI-integrated courses on academic performance and career adaptation, with student engagement and competency as mediating variables. A cross-sectional survey approach was adopted to collect data and evaluate the proposed conceptual model.

Participants and Sampling

The study was conducted among students enrolled in TVET institutions in Phnom Penh, Cambodia. Participants were selected from three TVET institutions, representing different academic programs and specializations, such as tourism and hospitality programs. The study involved 765 students. Purposive sampling and snowball sampling were used. Purposive sampling was first applied to identify TVET institutions and students who were actively enrolled in AI-related or technology-supported learning environments and were therefore able to provide relevant responses regarding AI-integrated courses. Snowball sampling was then used by asking initial respondents to distribute the questionnaire to other eligible TVET students within their academic networks, thereby increasing respondent recruitment. The sample included students across different years of study and age groups, primarily aged between 14 and 19 years old, representing the major population of TVET learners in Cambodia.

Instrument Development

Data were collected using a structured questionnaire consisting of closed-ended items measured on a five-point Likert scale. The questionnaire included five constructs: AI-integrated courses (AIC), student engagement (SE), student competency (SC), academic performance (AP), and career adaptation (CA). AI-integrated courses were assessed using items measuring students' perceptions of AI integration in teaching and learning. Student engagement was measured using items capturing behavioral, cognitive, and emotional participation in learning activities. Student competency was measured using items assessing AI literacy, technical competence, and learning-related capabilities. Academic performance was measured using items assessing students' academic achievement and perceived learning outcomes. Career adaptation was measured using items assessing students' readiness and confidence in adapting to future career demands. To accommodate the TVET context and AI-integrated learning environment in Cambodia, survey items were adjusted from validated scales in earlier research. Particularly, AI-integrated courses are measured by 5 items adapted from prior studies conducted by Jerez et al. (2025) Davis (1989) and Chiu et al. (2025) focusing on AI-supported learning environments and perceived usefulness of AI in education, which assess the role of AI in enhancing academic effectiveness, providing learning feedback, and supporting individualized learning.

Student engagement is measured by 5 items adapted from studies conducted by Handelsman et al. (2005) and Fredricks et al. (2004) capturing cognitive engagement in learning activities. In addition, student competency with 5 items is adapted from D. Long and Magerko (2020) Chiu et al. (2025), which highlights personal abilities to effectively utilize AI tools, critically assess AI-generated information, and use AI technologies ethically.

Moreover, academic performance is measured by 5 items adapted from Richardson et al. (2012), focusing on assessing students' academic achievement, assignments, exams, and academic satisfaction. Furthermore, career adaptation is also measured by 5 items adapted from Savickas and Porfeli (2012), which emphasize students' confidence in challenging future career issues, students' ability to adapt to future careers, and new job environments. **Table 1** presents a summary of all measurement scales.

Table 1. Scales

Constructs		Items	Sources
AI-integrated Courses	AIC1	AI tools are integrated into my course learning activities.	(Jerez et al., 2025; Davis, 1989; Chiu et al., 2025)
	AIC2	AI technologies help me understand course contents more clearly and effectively.	
	AIC3	AI tools provide useful feedback for my learning and skill practices.	
	AIC4	AI technologies improve my learning experience in skill training course.	
	AIC5	AI technologies support individualized learning.	
Student Engagement	SE1	I engage actively in skill training course.	(Handelsman et al., 2005; Fredricks et al., 2004)
	SE2	I exert considerable effort in understanding training materials.	
	SE3	I like engaging in class discussions.	
	SE4	I pay attention during lectures and training activities.	
	SE5	I am motivated to learn the training materials.	
Student Competency	SC1	I can effectively utilize AI tools for my learning.	(D. Long & Magerko, 2020; Chiu et al., 2025)
	SC2	I can use AI technologies to solve problems.	
	SC3	I can assess AI-generated information.	
	SC4	I am aware of how AI technologies can be used ethically.	
	SC5	I have enough skills needed to work with AI technologies.	
Academic Performance	AP1	I achieve good grades in my study.	(Richardson et al., 2012)
	AP2	I do well on assignments and exams.	
	AP3	I am aware of training materials clearly.	
	AP4	I am satisfied with my academic achievement.	
	AP5	My learning outcomes meet my academic goals.	
Career Adaptation	CA1	I am confident in overcoming future career obstacles.	(Savickas & Porfeli, 2012)
	CA2	I am ready to adapt to changes in the labor market.	
	CA3	I actively look at career opportunities.	
	CA4	I think I can achieve my career goals.	
	CA5	I can adapt to different situations and new job roles.	

Pilot Testing

30 students participated in a pilot test to evaluate the validity, reliability, and clarity of the questionnaire items prior to the main data collection. The pilot study enhanced item readability and identified unclear phrasing. Cronbach's alpha was used to evaluate reliability, and all constructs showed satisfactory internal consistency above recommended thresholds.

Data Collection Procedure

Data were collected during March 2026 using Google Forms questionnaires. The questionnaire items were translated into Khmer to ensure that respondents clearly understood the survey content. Before distributing the questionnaire, permission was obtained from relevant TVET institutions. The purpose of the study was explained to respondents, and they were asked to voluntarily participate in the study. The questionnaire was distributed directly to students through institutional channels and student networks. To ensure data quality, participants were given enough time to finish the survey, and responses that contained response quality issues were not included in the analysis.

Ethical Considerations

This study was conducted in accordance with recognized ethical principles for academic research, with careful attention to protecting participants' rights, privacy, and well-being throughout the research process. Before participating, all respondents were clearly informed about the purpose of the study, the voluntary nature of their participation, and their right to decline or withdraw from the survey at any time without any negative consequences. Informed consent was obtained from each respondent prior to data collection.

To ensure confidentiality and anonymity, no personally identifiable information was collected, and all responses were treated with strict confidentiality. The collected data were securely stored and used solely for academic and research purposes. Access to the data was limited exclusively to the researcher, and findings were reported only in aggregated form to prevent the identification of individual respondents. Throughout the study, principles of transparency, respect, informed consent, and responsible data management were strictly maintained to uphold research integrity and ethical accountability.

Data Analysis Procedure

IBM SPSS Statistics 26 and SmartPLS 4 were used to analyze the collected data. IBM SPSS Statistics 26 was used to conduct data screening, demographic analysis, descriptive statistics, and reliability testing. This included examination of means, standard deviations, and internal consistency of all constructs. Additionally, measurement and structural models were evaluated using Partial Least Squares Structural Equation Modelling (PLS-SEM) with SmartPLS 4. The analysis included measurement model evaluation, including reliability and validity assessment; path analysis to evaluate direct relationships among constructs; mediation analysis to examine the indirect effects of student engagement and student competency; model explanatory power (R^2); Effect size (f^2); and predictive relevance (Q^2).

RESULTS

To produce reliable results, data analysis in this study was performed by conducting data screening and cleaning, respondent profiling, descriptive statistics for main variables, common method bias, and followed by measurement model assessments, full structural model assessments, as well as model explanatory power and predictive relevance assessments.

Data Screening and Cleaning

The dataset was screened and cleaned to ensure the quality of the data. Outliers, missing data, respondent misconduct, and invalid data were assessed using SPSS. The results showed that there were no missing values or impermissible responses. Outlier detection was performed using boxplot analysis, which identified extreme outliers in items SE1, SE2, and CA2–CA5. These outliers were investigated further to see if they were the consequence of incorrect data entry or if they were real but extreme participant replies. The review confirmed that these values were valid responses rather than coding or entry errors. Moreover, additional reliability and validity assessments indicated that retaining these items did not negatively affect the internal consistency or construct validity of student engagement (SE) and career adaptation (CA). Therefore, the outlier cases were retained in the dataset to preserve data authenticity and variability. To identify potential low-quality responses or respondent misconduct, individual response patterns were examined using standard deviation analysis. Following established screening practices, respondents with within-response standard deviations below 0.25 were considered to demonstrate insufficient response variation, suggesting possible straight-lining or inattentive answering. Based on this criterion, 109 respondents were removed from the dataset. Because this represents a substantial proportion of the original sample, additional comparisons were conducted between the retained and deleted respondents based on key demographic characteristics, including gender and age. The comparisons revealed no substantial differences between the groups, suggesting that respondent removal did not introduce significant sample bias. As a result of the screening and cleaning process, the final analytical sample consisted of 656 valid responses, which were used for subsequent statistical analyses and model testing.

Respondent Profile

The sample comprised 656 TVET students, including 302 males (46%) and 354 females (54%). Most respondents were aged 14–19 (73.2%) and 20–25 (24.8%), followed by 26–31 (1.1%), 32–37 (0.2%), 38–43 (0.3%), and ≥ 44 (0.5%).

Descriptive Statistics for Main Variables

The descriptive statistics (see **Table 2**) showed that TVET students perceived AI-integrated courses at a moderate level (M = 3.468, SD = 0.720), with the strongest perceptions on improved understanding (AIC2) and feedback support (AIC3), while individualized learning and learning experience improvements were rated slightly lower. Student engagement was the highest construct (M = 4.033, SD = 0.645), indicating strong participation, motivation, and attention in learning activities. Student competency was moderate (M = 3.355, SD = 0.683), with better perceptions in AI tool use and ethics, but weaker skills in evaluating AI-generated information and overall AI capability. Academic performance was moderately high (M = 3.770, SD = 0.654), reflecting satisfactory achievement and goal attainment, while career adaptation was high (M = 3.927, SD = 0.669), showing strong confidence in future career readiness and adaptability. Overall, the findings revealed that while AI-integrated courses and student competency were perceived at moderate levels, students demonstrated high engagement, strong academic performance, and a high level of confidence in adapting to future careers in the AI era.

Common Method Bias

Common method bias was checked using the variance inflation factor (VIF). A VIF value of more than 3.3 indicates pathological collinearity, which could be a sign that common method bias has tainted the model (Kock, 2015). The results of collinearity statistics revealed that all values of VIF were less than 3.3 (see **Table 3**). Hence, there was no issue of common method bias in this study.

Table 2. Descriptive Statistics for Main Variables

Items	Mean (M)	Std. Deviation (SD)
AIC1	3.428	0.878
AIC2	3.578	0.901
AIC3	3.523	0.859
AIC4	3.401	0.904
AIC5	3.412	0.907
AIC	3.468	0.720
SE1	3.985	0.787
SE2	3.938	0.766
SE3	4.070	0.790
SE4	4.130	0.764
SE5	4.043	0.768
SE	4.033	0.645
SC1	3.526	0.839
SC2	3.384	0.862
SC3	3.209	0.884
SC4	3.419	0.841
SC5	3.239	0.885
SC	3.355	0.683
AP1	3.701	0.769
AP2	3.713	0.770
AP3	3.733	0.744
AP4	3.883	0.806
AP5	3.817	0.814
AP	3.770	0.654
CA1	3.829	0.804
CA2	3.916	0.772
CA3	3.919	0.790
CA4	3.976	0.793
CA5	3.992	0.771
CA	3.927	0.669

Note: M = Mean, SD = Standard Deviation, AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

Table 3. Variance Inflation Factors for Common Method Bias

Path of Constructs	Variance Inflation Factor (VIF)
AIC -> AP	1.547
AIC -> CA	1.547
AIC -> SC	1.000
AIC -> SE	1.000
SC -> AP	1.587
SC -> CA	1.587
SE -> AP	1.059
SE -> CA	1.059

Note: VIF = Variance Inflation Factor, AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

Measurement Model Assessment

Measurement model assessment (see **Figure 2**) was conducted to assess the quality of constructs in the study, which focuses on factor loading assessment followed by indicator multicollinearity, reliability, and validity assessments. Statistics revealed that all factor loadings exceeded the threshold value of 0.50, with most of them being over the preferred value of 0.70. Hence, all factor loadings of all constructs were satisfied. Multicollinearity of constructs was analyzed using the Variance Inflation Factor (VIF). The results revealed that all values of VIF less than 5 indicated no multicollinearity problems (Hair et al., 2021). Cronbach's alpha and composite reliability of all constructs were greater than 0.70.

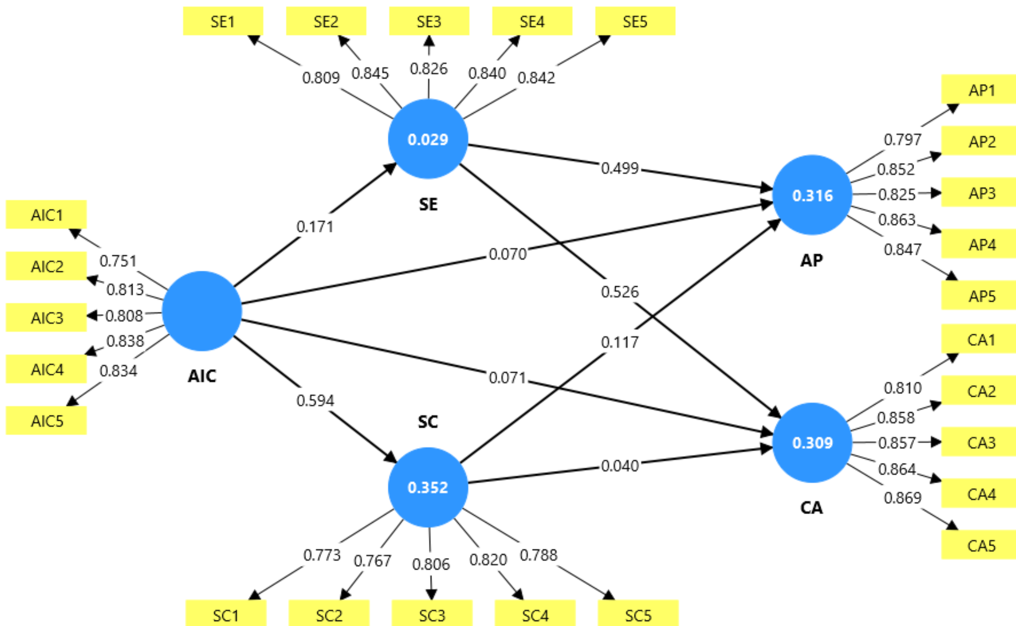

Figure 2. Measurement Model (Source: The author)

Thus, the reliability of constructs was established. In addition, convergent validity was also established with Average Variance Extracted (AVE) values above 0.50. Factor loadings, multicollinearity of constructs, reliability, and convergent validity are shown in **Table 4**.

Table 4. Assessment of Factor Loadings, Multicollinearity, Reliability, and Convergent Validity

Constructs	Items	Outer loadings	Variance Inflation Factor (VIF)	Cronbach's alpha	Composite reliability	Average variance extracted (AVE)
AI-Integrated Courses	AIC1	0.751	1.639	0.868	0.905	0.655
	AIC2	0.813	1.918			
	AIC3	0.808	1.979			
	AIC4	0.838	2.198			
	AIC5	0.834	2.168			
Student Engagement	SE1	0.809	2.181	0.889	0.919	0.693
	SE2	0.845	2.418			
	SE3	0.826	2.161			
	SE4	0.840	2.239			
	SE5	0.842	2.360			
Student Competency	SC1	0.773	1.694	0.851	0.893	0.626
	SC2	0.767	1.789			
	SC3	0.806	2.110			
	SC4	0.820	2.100			
	SC5	0.788	1.838			
Academic Performance	AP1	0.797	2.009	0.893	0.921	0.701
	AP2	0.852	2.434			
	AP3	0.825	2.112			
	AP4	0.863	2.768			
	AP5	0.847	2.602			
Career Adaptation	CA1	0.810	2.085	0.905	0.930	0.726
	CA2	0.858	2.542			
	CA3	0.857	2.451			
	CA4	0.864	2.854			
	CA5	0.869	2.835			

Note: VIF = Variance Inflation Factor, AVE = Average Variance Extracted, AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

Furthermore, discriminant validity was assessed using the Fornell–Larcker criterion and the HTMT ratio. Statistics revealed that each construct had the square root of AVE greater than its correlation with other constructs, and all HTMT values were below the threshold of 0.85, as shown in **Table 5**. Hence, there were no discriminant validity issues in this study.

Structural Model Assessment

Following the measurement model assessment, structural model assessment was conducted by rechecking the multicollinearity, examining the relationship path analyses between AI-integrated courses, student engagement, student competency, academic performance, and career adaptation, as well as the mediating effects of student engagement and competency on these relationships. Bootstrapping using 10,000 subsamples procedure was performed to analyze and produce the statistical results of structural model assessment.

Multicollinearity Test

Before assessing the relationship paths, the collinearity was reconfirmed by assessing the variance inflation factor (VIF) values of the constructs. The collinearity of variance inflation factor values indicated that no VIF values were greater than 5 (see **Table 3**). Hence, there were no collinearity issues in this study.

Path Analysis

This study examined the relationships between AI-integrated courses, student engagement, student competency, academic performance, and career adaptation. The path analysis results (**Table 6**) showed that AI-integrated courses did not have a significant direct effect on academic performance ($\beta = 0.070$, $t = 1.506$, $p = 0.132$, not supporting H1a) and career adaptation ($\beta = 0.071$, $t = 1.505$, $p = 0.132$, not supporting H1b), indicating no direct influence on these outcomes. However, AI-integrated courses significantly affected student engagement ($\beta = 0.171$, $t = 3.810$, $p < 0.001$, supporting H1c) and student competency ($\beta = 0.594$, $t = 17.529$, $p < 0.001$, supporting H1d).

Table 5. Fornell-Larcker Criterion, and Heterotrait-Monotrait Ratio

	AIC	AP	CA	SC	SE
AIC	***0.809***	0.255	0.207	0.686	0.193
AP	0.224	***0.837***	0.703	0.313	0.602
CA	0.185	0.633	***0.852***	0.228	0.609
SC	0.594	0.274	0.204	***0.791***	0.262
SE	0.171	0.538	0.547	0.232	***0.833***

Note: Bold, diagonal, and italicized elements are the square roots of Average Variance Extracted-AVE. Below the diagonal ones are the correlations between the values of constructs (Fornell & Larcker Criterion), and above are the values of Heterotrait-Monotrait Ratio-HTMT, AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

Table 6. Path Analysis

Hypotheses	β	T statistics	P values	Results
H1a: AIC -> AP	0.070	1.506	0.132	Not Supported
H1b: AIC -> CA	0.071	1.505	0.132	Not Supported
H1c: AIC -> SE	0.171	3.810	0.000	Supported
H1d: AIC -> SC	0.594	17.529	0.000	Supported
H2a: SE -> AP	0.499	10.841	0.000	Supported
H2b: SE -> CA	0.526	12.001	0.000	Supported
H3a: SC -> AP	0.117	2.273	0.023	Supported
H3b: SC -> CA	0.040	0.746	0.456	Not Supported

Note: β = Beta Coefficient, AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

Student engagement significantly influenced academic performance ($\beta = 0.499$, $t = 10.841$, $p < 0.001$, supporting H2a) and career adaptation ($\beta = 0.526$, $t = 12.001$, $p < 0.001$, supporting H2b). Student competency significantly affected academic performance ($\beta = 0.117$, $t = 2.273$, $p = 0.023$, supporting H3a) but not career adaptation ($\beta = 0.040$, $t = 0.746$, $p = 0.456$, not supporting H3b). Overall, the results highlighted that student engagement was the most influential factor affecting both academic performance and career adaptation, while student competency played a more limited role, particularly in relation to career adaptation. Importantly, the non-significant direct effects of AI-integrated courses on academic performance and career adaptation, combined with their significant effects on engagement and competency, suggested the presence of indirect (mediated) relationships. This implied that AI-integrated courses contributed to improved academic and career outcomes primarily through enhancing student engagement and competency rather than through direct effects.

Mediation Analysis

The mediation analysis provided further evidence on how AI-integrated courses influenced academic performance and career adaptation through student engagement and competency. The results (see **Table 7**) showed that student engagement significantly mediated both relationships, with AI-integrated courses having significant indirect effects on academic performance ($\beta = 0.085$, $t = 3.299$, $p = 0.001$, supporting H4a) and career adaptation ($\beta = 0.090$, $t = 3.406$, $p = 0.001$, supporting H4b). This indicated that AI-integrated courses enhanced both outcomes by increasing student engagement. Student competency also significantly mediated the relationship between AI-integrated courses and academic performance ($\beta = 0.069$, $t = 2.221$, $p = 0.026$, supporting H5a), but not career adaptation ($\beta = 0.024$, $t = 0.738$, $p = 0.461$, not supporting H5b), showing a limited mediating role. Further examination of the total and direct effects strengthens this interpretation. The total effects of AI-integrated courses on academic performance ($\beta = 0.224$, $p < 0.001$) and career adaptation ($\beta = 0.185$, $p < 0.001$) were both significant, indicating that AI-integrated courses had an overall meaningful impact on these outcomes.

However, the direct effects on academic performance ($\beta = 0.070$, $p = 0.132$) and career adaptation ($\beta = 0.071$, $p = 0.132$) were not significant. This pattern indicated full mediation through student engagement for both academic performance and career adaptation, while student competency provided an additional mediating pathway only for academic performance. Overall, the findings highlighted that student engagement was the most critical mechanism through which AI-integrated courses improved both academic performance and career adaptation. In contrast, student competency played a more limited but meaningful mediating role, contributing only to academic performance.

Table 7. Mediation Analysis

Hypotheses	β	T statistics	P values	Results
Indirect Effects				
H4a: AIC -> SE -> AP	0.085	3.299	0.001	Supported
H4b: AIC -> SE -> CA	0.090	3.406	0.001	Supported
H5a: AIC -> SC -> AP	0.069	2.221	0.026	Supported
H5b: AIC -> SC -> CA	0.024	0.738	0.461	Not Supported
Total Effects				
AIC -> AP	0.224	5.290	0.000	
AIC -> CA	0.185	4.380	0.000	
Direct Effects				
AIC -> AP	0.070	1.506	0.132	
AIC -> CA	0.071	1.505	0.132	

Note: β = Beta Coefficient, AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

These results emphasized that the effectiveness of AI integration in TVET education depended not only on the availability of AI technologies but also on how such technologies actively engaged students and supported the development of relevant competencies.

Model Explanatory Power and Predictive Relevance

The assessment of model explanatory power and predictive relevance indicated that the proposed model had moderate explanatory and acceptable predictive capability. The R^2 results showed that the model explained 31.6% of academic performance ($R^2 = 0.316$) and 30.9% of career adaptation ($R^2 = 0.309$), indicating moderate explanatory power. It also explained 35.2% of student competency ($R^2 = 0.352$), while only 2.9% of student engagement ($R^2 = 0.029$) was explained, suggesting weak explanatory power for engagement and the influence of other external factors.

The effect size (f^2) results showed that AI-integrated courses had a large effect on student competency ($f^2 = 0.544$), but only small effects on academic performance ($f^2 = 0.005$) and career adaptation ($f^2 = 0.005$). Student engagement had a large effect on academic performance ($f^2 = 0.344$) and career adaptation ($f^2 = 0.378$), making it the most influential predictor, while student competency showed a small effect on academic performance ($f^2 = 0.013$) and a negligible effect on career adaptation ($f^2 = 0.001$).

Regarding predictive relevance, all Q^2 values were above zero—academic performance (0.046), career adaptation (0.030), student engagement (0.024), and student competency (0.347)—indicating acceptable predictive relevance, with the strongest prediction for student competency. Overall, the results indicated that the model had moderate explanatory power and adequate predictive relevance, with student engagement emerging as the most critical driver of academic performance and career adaptation. AI-integrated courses played a significant role in enhancing student competency, which contributed indirectly to academic performance, while their direct impact on performance and career adaptation remained limited. These findings reinforced the importance of engagement and competency as key mechanisms through which AI integration influenced student outcomes in TVET education. R-square, F-square, and Q-square are presented in **Table 8**.

DISCUSSION

This study examined how AI-integrated courses influence academic performance and career adaptation among TVET students through the mediating roles of student engagement and student competency. The findings revealed that AI-integrated courses did not directly influence academic performance and career adaptation, which contrasts with prior studies in higher education contexts (e.g., Merino-Campos, 2025). This suggests that, in the TVET context, the presence of AI technology alone may not automatically lead to better academic or career outcomes.

Table 8. R-Square, F-Square, Q-Square

Exogenous Constructs	Endogenous Constructs	R-square	f-square	Q-square
AIC -> AP	AP	0.316	0.005	0.046
SE -> AP			0.344	
SC -> AP			0.013	
AIC -> CA	CA	0.309	0.005	0.030
SE -> CA			0.378	
SC -> CA			0.001	
AIC -> SE	SE	0.029	0.030	0.024
AIC -> SC	SC	0.352	0.544	0.347

Note: AIC = AI-Integrated Courses, SE = Student Engagement, SC = Student Competency, AP = Academic Performance, CA = Career Adaptation

Instead, the effectiveness of AI integration depended on how students interact with and benefit from these technologies through active engagement and competency development. This may reflect the practical and applied nature of TVET education, where learning outcomes depended not only on access to digital tools but also on students' readiness and ability to use them meaningfully.

Consistent with Social Cognitive Theory (Bandura, 1986), AI-integrated courses significantly enhanced both student engagement and student competency, confirming that learning environments can shape students' behaviors, motivation, and skill development. Notably, AI-integrated courses showed a much stronger effect on student competency than on student engagement. This finding suggests that AI tools may be particularly effective in helping students develop technical skills, AI literacy, problem-solving abilities, and critical thinking through personalized feedback, adaptive learning support, and practical simulations. However, AI integration alone may not be sufficient to increase student engagement to the same extent. One explanation is that engagement depends heavily on broader pedagogical and motivational conditions, such as teaching style, classroom interaction, learner autonomy, and the quality of AI tool design. For example, if AI is used primarily as an instructional support tool rather than an interactive or collaborative learning platform, students may improve their competencies without necessarily feeling more emotionally or cognitively engaged. In addition, unequal access to digital devices, limited internet connectivity, or insufficient training in using AI tools may reduce students' ability to fully engage with AI-supported learning environments, particularly in Cambodian TVET settings.

The findings further confirmed the central role of student engagement, which emerged as the strongest predictor of both academic performance and career adaptation. This aligns with Self-Determination Theory (Ryan & Deci, 2000), which emphasizes that students who are actively involved, motivated, and attentive in their learning are more likely to achieve positive educational and developmental outcomes. Highly engaged students may invest more effort in learning tasks, seek deeper understanding, and demonstrate greater persistence when facing academic or career-related challenges. The strong relationship between engagement and career adaptation also suggests that behavioral, emotional, and cognitive involvement in learning helps students build confidence, career awareness, and adaptability for future labor market demands.

In contrast, although student competency significantly predicted academic performance, it did not significantly influence career adaptation. This finding suggests that technical and AI-related competencies alone may not be sufficient to prepare students for dynamic and uncertain career environments. Career adaptation, as explained by Career Construction Theory (Savickas, 2013), involves broader psychosocial resources such as career concern, control, curiosity, and confidence. While AI competency may improve students' academic capabilities, adapting successfully to future careers may also require soft skills, workplace exposure, career guidance, professional identity development, and opportunities for industry-linked learning. TVET students may possess growing technical skills but still lack confidence in applying these skills in real employment settings or navigating rapidly changing labor market expectations. This may explain why competency alone did not translate into stronger career adaptability.

The mediation analysis provided further insight into these mechanisms. Student engagement fully mediated the relationships between AI-integrated courses and both academic performance and career adaptation, indicating that engagement was the primary pathway through which AI integration creates meaningful outcomes. This suggests that AI technologies are most effective when they actively stimulate students' participation, motivation, and involvement in learning. Student competency also mediated the relationship between AI-integrated courses and academic performance, but not career adaptation, reinforcing its more limited and academically focused role. These findings extend Career Construction Theory by demonstrating that career adaptability may depend more on motivational and behavioral engagement than on technical competence alone.

Finally, the model demonstrated moderate explanatory power and acceptable predictive relevance, supporting its usefulness in explaining student outcomes in the TVET context. The particularly strong effect size of student engagement highlighted its strategic importance for educators and institutions seeking to maximize the benefits of AI integration. Overall, this study contributes to the literature by offering a comprehensive and integrated model explaining how AI-integrated courses influence both academic and career outcomes in the underexplored TVET context. More importantly, it shifts the focus from a technology-centered perspective to a learner-centered perspective, emphasizing that the success of AI integration depends less on the technology itself and more on how effectively it fosters student engagement and develops meaningful competencies.

CONCLUSION

This study investigated the effects of AI-integrated courses on academic performance and career adaptation among TVET students, with student engagement and student competency as mediating variables. The findings revealed that AI-integrated courses did not directly influence academic performance or career adaptation; rather, their effects are primarily transmitted through student engagement and, to a lesser extent, student competency.

Among the mediators, student engagement emerged as the most influential factor, significantly enhancing both academic performance and career adaptation and fully mediating the effects of AI-integrated courses on these outcomes. Student competency also contributed significantly to academic performance, but it did not significantly predict career adaptation, suggesting that technical and AI-related skills alone may not be sufficient to prepare students for dynamic labor market demands. These findings demonstrated that the success of AI integration in TVET depends not only on technological availability but also on how effectively AI-supported learning environments foster active participation, motivation, and meaningful competency development. By offering an integrated framework based on Social Cognitive Theory, Self-Determination Theory, and Career Construction Theory, this study adds to the expanding body of research on AI in education, particularly in the understudied setting of Cambodian TVET education. The findings highlighted that engagement-driven learning is the key mechanism linking AI-integrated courses to student success in both academic and career domains.

PRACTICAL IMPLICATIONS

The findings offer key stakeholders involved in AI integration in TVET education several practical implications.

TVET institutions should move beyond simply adopting AI technologies and focus on creating interactive, student-centered AI learning environments that promote active engagement and practical skill development. Investments in digital infrastructure, reliable internet access, and institutional AI readiness are essential to ensure effective implementation.

Teachers and trainers play a critical role in transforming AI tools into meaningful learning experiences. They should be trained to integrate AI pedagogically by combining AI-supported instruction with collaborative learning, feedback, and learner autonomy to strengthen student engagement and motivation.

AI should be included in curricula as both a technical subject and an integrated learning tool for TVET programs. To better enhance professional preparedness, AI-integrated curricula should strike a balance between developing technical competencies and soft skills like flexibility, problem-solving, communication, and critical thinking.

For the proper integration of AI in TVET systems, educational policymakers should provide explicit national strategies and guidelines. Policy support should include teacher capacity building, equitable digital access, ethical AI use frameworks, and stronger alignment between TVET curricula and industry workforce demands in the AI era.

Future studies should further investigate additional factors influencing student engagement and career adaptation, such as teaching quality, learner autonomy, digital access, and institutional support, to build a more comprehensive understanding of AI adoption in vocational education.

LIMITATIONS AND FUTURE RESEARCH DIRECTIONS

This study has several limitations that should be recognized despite its merits. First, using a cross-sectional research design makes it more difficult to determine the variables' causal links. Future longitudinal or experimental studies are needed to better examine how AI-integrated learning influences student outcomes over time. Second, academic performance was measured through self-reported perceptions, which may not fully reflect students' actual academic achievement. Future research should incorporate objective indicators such as examination scores or institutional academic records. Third, the sample was limited to TVET institutions in Phnom Penh, Cambodia, which may restrict the generalizability of the findings to other regions or educational contexts. Expanding the study to rural areas or other countries would improve external validity. Fourth, the use of purposive and snowball sampling may introduce selection bias and further limit generalizability. Probability-based sampling approaches should be considered in future studies. Fifth, the study assessed AI-integrated courses broadly without distinguishing the specific type, intensity, or quality of AI integration (e.g., AI tutoring systems, chatbots, simulations, or assessment tools). Future research should examine how different forms of AI use may produce different educational outcomes. Sixth, although statistical procedures were applied to reduce bias, common method bias may still be present because all variables were collected through the same self-report survey.

Finally, the low explanatory power for student engagement ($R^2 = 0.029$) suggests that important predictors of engagement were not included in the model. Additional variables such as teaching style, perceived usefulness of AI, student autonomy, digital confidence, and institutional support should be explored in future studies. Overall, while this study provides important insights into AI integration in TVET education, future research should continue refining and expanding the model to better understand how AI can support both academic success and long-term career adaptability.

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Ethical Statement: The study followed established ethical standards for educational research. Participation was voluntary, with informed consent obtained from all participants after explaining the study purpose, procedures, risks, and benefits. Confidentiality and anonymity were strictly maintained, with no identifying information collected. Data were securely stored and accessible only to the researchers. Participants could withdraw at any time without penalty. The study avoided coercion or deception and adhered to principles of honesty, transparency, and integrity in data collection, analysis, and reporting.

Data Availability: The data that support the findings of this study are available from the corresponding author upon reasonable request.

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