International Review of Management and Marketing

ISSN: 2146-4405

available at http: www.econjournals.com

International Review of Management and Marketing, 2026, 16(6), 89-98.

Artificial Intelligence Enabled Learning as a Driver of Workforce Readiness in Hospitality and Tourism

Janry Paul A. Santos, Mark Alvin H. Abad*

Nueva Ecija University of Science and Technology, Cabanatuan City, Philippines. *Email: travelsmoker84@gmail.com

Received: 01 March 2026 **Accepted:** 29 June 2026 **DOI:** https://doi.org/10.32479/irmm.23411

ABSTRACT

The integration of artificial intelligence-enabled learning into higher education has redefined the teaching and learning environment, especially in vocational disciplines such as hospitality and tourism. This study investigates the direct and indirect effects of Artificial Intelligence-enabled learning on workforce readiness among hospitality and tourism students in the Philippines. The psychological mediators of learning engagement and self-efficacy were examined using data from 300 students, with analyses conducted using covariance-based structural equation modeling. The study's findings suggest that artificial intelligence-enabled learning enhances workforce preparedness, both indirectly and directly, by boosting learning engagement and self-efficacy. This validated mediated structural model provides theoretical insight into employability research and expands on the artificial intelligence-enabled learning literature in an emerging economy setting. The structural model explained 44% of the variance in workforce readiness, indicating moderate explanatory power within the proposed framework. Implications for curriculum design and workforce preparedness in hospitality and tourism education are discussed.

Keywords: Artificial Intelligence-enabled Learning, Workforce Readiness, Hospitality and Tourism Education, Employability, Learning Engagement

JEL Classifications: I23, J24

1. INTRODUCTION

The hospitality and tourism business practice in the artificial intelligence era has been revolutionized by the introduction of artificial intelligence, online marketplaces, and data-driven networks, which are affecting service delivery, operations, and the workforce (Gu et al., 2026). In view of today's technology-oriented service environment and the growing demands from customers, there is now a greater focus on workforce readiness as an antecedent of service excellence, adaptability, and future competitiveness, particularly in the hospitality and travel industry (Nguyen and Chiu, 2023). Current work readiness comprises not only technical basics but also service communication skills, problem-solving ability, digital savviness, and career confidence needed to undertake a job with a modern service component.

Skill gaps in service decision-making, adaptability, and the effective use of digital tools in operations have been well documented (Liu et al., 2023). Workforce training can fill these gaps by teaching experiential skill acquisition, planning for ongoing feedback and accountability, and connecting course outcomes with service delivery in the field by a diverse workforce.

Artificial intelligence-enabled learning has evolved into a workforce development tool that can facilitate skill development and workforce readiness in service-led sectors (Laundon et al., 2023). By using tools such as personalized feedback systems and intelligent simulations of service transactions that can support trainees, an artificial intelligence-enabled learning environment can help develop authentic skill practices much like those found in work situations within the hospitality and tourism industry. However, rather than being only a pedagogical innovation,

This Journal is licensed under a Creative Commons Attribution 4.0 International License

artificial intelligence-enabled learning is framed as an investment in human capital, empowering people to acquire capabilities that are elicited by workplace performance, service excellence, and digital collaboration (Wan and Gu, 2025).

Although there is mounting scholarly interest in the adoption of artificial intelligence in education and literature on artificial intelligence applications within hospitality and tourism operations, empirical studies that specifically investigate the influence of artificial intelligence-enabled learning on workforce readiness are scarce (Hafeez et al., 2026). Previous research has tended to focus on acceptance, satisfaction, and efficiency, with less attention to employability outcomes and professional practice readiness (Cheung et al., 2025). Also, hospitality and tourism sector-specific studies that integrate Artificial Intelligence-enabled capability development with workforce readiness, especially in emerging and developing economies, are scarce. It is this gap that limits theoretical development and the need to make productive, research-led decisions about workforce planning and talent management.

Even though artificial intelligence technologies are increasingly integrated into higher education, few studies have empirically investigated the outcomes of employing artificial intelligence-enabled learning environments in preparing students for the real world in hospitality and tourism education (Baluyut, 2025). Where previous research has focused on new digital learning tools and employability, we still have an inadequate understanding of how artificial intelligence-enabled learning leads to work readiness, that is, the underlying psychological processes (Singh et al., 2025).

Specifically, the mediating functions of learning engagement and self-efficacy in hospitality and tourism settings are not yet well investigated (Alam et al., 2023). Given the knowledge-based nature of this industry, it is necessary to understand these processes, as this enables academic backgrounds to align with the labor market's requirements.

Despite the increased use of artificial intelligence-based platforms in higher education, there is limited empirical evidence on how artificial intelligence-enabled learning translates into measurable workforce-readiness outcomes in hospitality and tourism education within emerging economies (Gu et al., 2026). This lack of empirical/theoretical focus hampers artificial intelligence research and the development of curricula and policies grounded in sound evidence.

More importantly, existing studies have tended to focus either on artificial intelligence adoption or on satisfaction, thereby limiting a deeper understanding of the psychological and pedagogical processes underlying how artificial intelligence learning influences employability-related competences (Kong et al., 2025). The dearth of mediated structural modeling in the context of hospitality and tourism education prevents theoretical clarity on how engagement and self-efficacy serve as developmental pathways that connect instructional technology to workforce readiness (Mughal et al., 2024).

There is relatively little information on how and why artificial intelligence-enabled learning would manifest in workforce readiness across the student body of hospitality and tourism through the mediating constructs of learning engagement and self-efficacy (Alam et al., 2023). Emphasizing an emerging economy adds contextual specificity to international discussions on the transformation of artificial intelligence-based curricula and the development of employability (Wut et al., 2025).

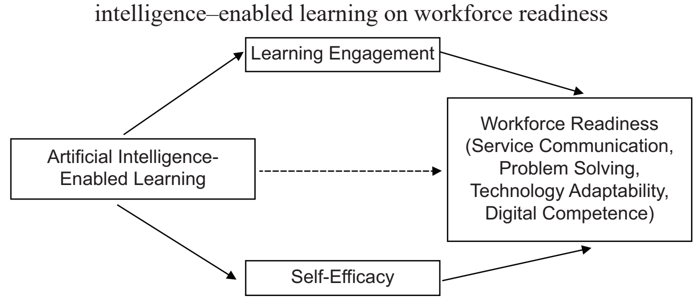
1.1. Conceptual Framework

A structured incorporation of artificial intelligence-driven tools, such as adaptive systems, intelligent feedback methods, simulation environments, and generative artificial intelligence applications, into pedagogy to enhance personalization, interaction, and performance-oriented experiences. In the context of hospitality and tourism education, artificial intelligence-enabled learning helps learners experience a technology-driven service environment that is traditionally offered in real industry practice (Gu et al., 2026).

The conceptual underpinnings of the study, social cognitive theory and engagement theory, enable us to hypothesize about the direct and indirect relationships between artificial intelligence-enabled learning and workforce readiness through psychological mechanisms (Han, 2024). That is, learning engagement and self-efficacy are considered immediate mediators through which exposure to technology-enhanced instruction leads to perceived preparedness (Figure 1).

Learning engagement is defined as students' cognitive and emotional participation in Artificial Intelligence-enabled learning. Self-efficacy refers to students' confidence in performing academic and industry-related work through technology-based systems (Liao et al., 2025). Workforce readiness represents students' perceived ability to discuss service issues, problem-solve, adapt to technology, and be digitally competent in tourism and hospitality. Learning engagement and self-efficacy were considered mediating variables, as they are proximal psychological constructs that connect instructional design to professional readiness (Bandura, 1997; Fredricks et al., 2004; Kahu, 2013). Although other factors, such as Artificial Intelligence literacy, technology attitudes, or institutional readiness, influence outcomes, engagement, and self-efficacy, engagement and self-efficacy are theoretically considered the most proximal determinants of skill internalization and performance confidence. If we focus on these mediators, we will achieve theoretical parsimony while retaining the structural model's explanatory power (Bandura, 1997; Kahu, 2013).

Figure 1: Research paradigm showing the influence of artificial intelligence–enabled learning on workforce readiness



1.2. Hypothesis

According to the underlying theoretical framework, the following hypotheses were tested:

H_1: Artificial intelligence-enabled learning has a significant positive impact on workforce readiness.

H_2: Artificial intelligence-enabled learning has a positive impact on learning engagement.

H_3: Artificial intelligence-enabled learning has a positive impact on self-efficacy.

H_4: Learning engagement significantly positively influences workforce readiness.

H_5: Self-efficacy has a direct positive influence on workforce readiness.

H_6: Learning engagement partially mediates the influence of Artificial Intelligence-enabled learning on work readiness.

H_7: Self-efficacy mediates the link between artificial intelligence-enabled learning and work preparedness.

1.3. Research Problems

1. What is the status quo of artificial intelligence-enabled learning in hospitality and tourism education in:
   a. Learning engagement
   b. Self-efficacy
   c. Digital employability skills
2. How would one describes the readiness of hospitality and tourism students for the workplace in respect of:
   a. Service communication competence
   b. Problem-solving ability
   c. Fit in technology-oriented working environments
   d. Digital competence
3. Is there a significant association between artificial intelligence-based learning and employability in the hospitality and tourism industry?
4. Are learning engagement and self-efficacy significant mediators in the relationship between artificial intelligence-enabled learning and workforce readiness?
5. Based on the findings, what Artificial Intelligence-enabled learning strategies may be recommended to strengthen workforce readiness?

2. RESEARCH METHODOLOGY

2.1. Research Design

This study used a quantitative, cross-sectional, correlational research design to explore how artificial intelligence-enabled learning was associated with workforce readiness in hospitality and tourism. Elshaer et al. (2025) employed a quantitative, cross-sectional correlational design to investigate connections between critical factors in professional terms and justify the use of this design for testing the relationship between artificial intelligence empowered learning and employability skills and readiness in hospitality management tourism education. The design was considered suitable, as it enables the systematic quantification of variables and the statistical analysis of relationships and mediation effects at a single time point. Quantitative techniques have been applied to produce an objective, transferable output by using numerical results from completing the survey.

Digital employability skills were descriptively assessed to provide information on students' perceived preparedness with technology in the context of Artificial Intelligence-enabled instruction (Wut et al., 2025). However, the variable was not included in the structural mediation model to prevent the construction of an over-specified, less theory-parsimonious model. This model was deliberately restricted to the examination of the posited psychological mechanisms underlying artificial intelligence-enabled learning and workforce preparedness. In a similar vein, treating digital employable skills as an additional endogenous construct alongside workforce readiness might have led to conceptual overlap with the workforce readiness dimensions, particularly digital competency, thereby undermining model parsimony and discriminant validity (Singh et al., 2025).

2.2. Participants and Research Locale

The respondents in the study were Bachelor of Science in Hospitality and Tourism Management students from colleges and universities in the Province of Nueva Ecija, Philippines. The sample size included 300 students.

Participants were enrolled hospitality and tourism management students who were formally registered in a hospitality and tourism management program at the time of data collection, and they assured that they volunteered to take part. Students who were absent on the day of data collection, withheld consent, or provided incomplete responses were excluded from the analysis. De Guzman et al. (2020) highlighted the need to invite only formally enrolled Hospitality and Tourism students to participate in studies and to avoid voluntary enrolment. They endorsed the prior use of specific inclusion and exclusion criteria to make the study sample valid, credible, and ethically sound.

2.3. Scope and Delimitations

Respondents of this study are hospitality and tourism management students at the chosen higher educational institution located in Nueva Ecija. There are some limitations to the study, such as the use of self-reported measures in a cross-sectional analysis, which cannot establish a cause-and-effect relationship. The results of the study must be applied to the province/school subject for which they were developed.

2.4. Sampling Technique

A proportional stratified random sampling method was used to ensure adequate representation of students in hospitality and tourism programs from each participating higher education institution. The total sample size was evenly allocated across the student populations at each university. Participants: The respondents in this study are currently hospitality/tourism students who are already exposed to AI-driven learning tools.

A total of 330 questionnaires were distributed, and for analysis, we used only 300 valid, complete surveys, yielding a response rate of 90.91%.

2.5. Research Instrument

Data were collected using a questionnaire specifically designed for the study, which included closed-ended questions (on a 4-point

Likert scale from 4 = strongly agree to 1 = strongly disagree). The instrument consisted of four sections designed to measure IAI-enabled learning, learning engagement, self-efficacy, and digital employability skills.

Workforce preparedness includes service communication, problem-solving, digital literacy, and technology-oriented skills.

A four-point Likert scale was used to minimize neutral responses and elicit clear responses from respondents.

Šulc et al. (2025) also indicated that well-defined endpoint anchors in closed-ended Likert scales promote response clarity and measurement consistency, which justifies the use of a 4-point Likert scale in the current study.

2.6. Validity of the Instrument

Experts in hospitality and tourism education, educational technology, and research methodology evaluated content validity. Five experts rated the relevance, clarity, and correlation with the study variables for each item. Proposed changes were made before data collection.

Content validity was established through pilot testing of the questionnaire on a sample of students similar to the study population to assess item clarity and intelligibility.

Factorial validity was evaluated through factor analysis during pretesting and/or complete data analysis to ensure that the items loaded on their relevant latent variables.

Goecke et al. (2025). If the items in a survey adequately represent the construct being measured, the survey has content validity, which supports our questionnaire's validation.

2.7. Reliability of the Instrument

Cronbach's alpha was calculated to assess the instrument's internal consistency reliability. A reliability coefficient of 0.70 was deemed acceptable for this construct. Based on back translation, items that did not contribute to measurement reliability were scrutinized and revised or deleted as required to ensure theoretical consistency.

2.8. Data Collection Procedure

The study was carried out with the approval of the relevant institutional authorities prior to data collection. Respondents were informed of its purpose, assured that all responses would be kept confidential, and given a consent form to sign.

Questionnaires were administered in written and digital formats, via an online survey platform, according to the institution's preference. Returned questionnaires were collected, checked for completeness, and readied for analysis.

As the data were cross-sectional and self-reported, procedural controls and statistical tests were used to address common method bias (Table 1). Anonymity and confidentiality were guaranteed, so the predictor, mediator, and outcome constructs were distributed across different sections of the questionnaire. Harman's single-factor test indicated that the first unrotated factor accounted for 34.62% of the total variance, below the 50% threshold, suggesting that common method bias is not a serious concern. In addition, full collinearity VIF values ranged from 1.42 to 2.36, which are below the conservative cut-off of 3.3. These results suggest that the common-method bias was not a serious threat to the study's validity.

Overall, the procedural and statistical evaluations suggest that common method bias does not significantly compromise the validity of the structural relationships observed in this study (Table 2).

Before determining the structural relationships, a confirmatory factor analysis was conducted to examine the measurement model within the structural equation modeling paradigm (Tables 3 and 4).

Table 1: Common method bias assessment

Test	Threshold	Obtained Value	Interpretation
Harman's Single Factor	<50% variance	34.62%	No serious CMB
Full Collinearity VIF (min-max)	<3.3	1.42-2.36	No collinearity concern

VIF: Variance inflation factor

Table 2: Measurement model assessment: Reliability and validity of constructs

Construct	Item	Standardized loading	Composite reliability (CR)	Average variance extracted (AVE)
Artificial intelligence–enabled learning (AIEL)	AIEL1	0.81	0.91	0.68
	AIEL2	0.83		
	AIEL3	0.84		
	AIEL4	0.85		
	AIEL5	0.79		
Learning engagement (LE)	LE1	0.78	0.88	0.60
	LE2	0.82		
	LE3	0.77		
	LE4	0.80		
	LE5	0.76		
Self-efficacy (SE)	SE1	0.80	0.89	0.62
	SE2	0.83		
	SE3	0.74		
	SE4	0.86		
	SE5	0.79		
Workforce readiness (WR)	WR1	0.84	0.92	0.69
	WR2	0.87		
	WR3	0.85		
	WR4	0.82		
	WR5	0.80		

Table 3: Discriminant validity assessment (Fornell–Larcker criterion)

Construct	AIEL	LE	SE	WR
AIEL	0.82			
LE	0.58	0.77		
SE	0.55	0.63	0.79	
WR	0.61	0.66	0.69	0.83

AIEL: Artificial intelligence–enabled learning, LE: Learning engagement, SE: Self-efficacy, WR: Workforce readiness

Item reliability was analyzed using standardized factor loadings, with re-loadings above 0.60; all items included in the final scale met the recommended threshold, indicating no problems with indicator reliability. Internal consistency was assessed using Composite Reliability, and all constructs exceeded 0.70, indicating high reliability. Convergent validity for all constructs was assessed using average variance extracted; scores of 0.50 or greater indicated that each latent variable explained more than half of its items' variance. These findings give evidence of the stability and convergent validity of the measurement model.

2.9. Data Preparation and Analysis

Structural equation modeling analyses were run in IBM Statistical Package for the Social Sciences AMOS version 26, and a covariance-based structural equation modelling with maximum likelihood estimation was used. Before the analysis, the data set was checked for missing values and outliers based on normality assumptions. Listwise deletion was used to handle missing data, yielding 300 valid cases. Model fit was tested through the chi-square to degrees of freedom ratio (χ^2/df), Comparative Fit Index, Tucker–Lewis Index, root mean square error of approximation, and standardized root mean square residual. An indirect effect was tested for mediation using the bootstrap method with 5,000 resamples and 95% confidence intervals. Statistical significance was tested at $P < 0.05$, in keeping with APA 7th edition reporting guidelines.

The same 4-point Likert scale and interpretation of mean scores were used to determine the extent of learning engagement (Table 5). The scale assessed the extent of students' engagement, curiosity, attention, and interest in artificial intelligence-enabled learning activities. The oral descriptions in the table are based on the mean values.

To assess Self-Efficacy, items from the questionnaire were constructed as statements asking students to express their confidence and perceived ability to complete tasks in learning through artificial intelligence platforms. The mean scores were interpreted within the same scale range, and the corresponding verbal descriptors can be taken to represent students' general level of self-efficacy.

Digital employability skills were measured through respondents' self-assessment of their use of digital tools and artificial intelligence in the workplace within hospitality and tourism. The status of the indexes was expressed on a Likert scale with scores of 4, and a verbal description of those score ranges was obtained from the mean-scored intervals.

Table 4: Heterotrait–Monotrait ratio

Construct	AIEL	LE	SE	WR
AIEL	–			
LE	0.69	–		
SE	0.65	0.72	–	
WR	0.74	0.78	0.76	–

AIEL: Artificial intelligence–enabled learning, LE: Learning engagement, SE: Self-efficacy, WR: Workforce readiness

Table 5: Scale interpretation of mean scores

Scale	Range	Verbal description
4	3.26-4.00	Very high
3	2.51-3.25	High
2	1.76-2.50	Low
1	1.00-1.75	Very low

The workforce readiness of hospitality and tourism management students was assessed through indicators across four dimensions: Service communication skills, problem-solving ability, adapting to a technology-based work context, and digital competencies. The same descriptions were applied to all dimensions and were derived from the calculated mean scores.

The artificial intelligence teaching model was evaluated by students using a 4-point Likert scale. A summary table presented the mean, standard deviation, and corresponding verbal description that depict students' acceptance and support levels of the artificial intelligence embedded teaching model in Hospitality and Tourism education.

2.10. Ethical Considerations

This study was conducted in accordance with the ethical standards for research involving human subjects. Permission had been taken from the concerned institutional ethical committee before data collection. The study was voluntary, and all respondents provided written consent. No personal data was reported, and all information was rendered anonymous with confidentiality assured. All collected data were for academic research use only. The study complied with institutional and national ethical standards for academic research.

3. RESULT AND DISCUSSION

3.1. Profile of the Respondents

The demographic profile of the respondents is described to understand better and interpret the findings (Table 6). The

Table 6: Demographic characteristics of the respondents (n=300)

Variable	Category	Frequency (n)	Percentage
Age	18-19 years	72	24.0
	20-21 years	128	42.7
	22-23 years	74	24.7
	24 years and above	26	8.6
Sex	Male	126	42.0
	Female	168	56.0
	Prefer not to say	6	2.0
Year level	1st year	78	26.0
	2nd year	82	27.3
	3rd year	75	25.0
	4th year	65	21.7
Type of institution	Public University/College	184	61.3
	Private University/College	116	38.7
Prior exposure to artificial intelligence-enabled learning technologies	None	38	12.7
	Limited exposure	96	32.0
	Moderate exposure	112	37.3
	Extensive exposure	54	18.0

respondent profile was detailed by age, sex, year level, type of institution attended, and prior exposure to Artificial Intelligence-enabled learning technologies. This profiling provides transparency into sample characteristics and helps generalize the results.

Demographic data for our sample, presented for ease of understanding, are shown in Table 6. The majority of participants reported an age of 20-21 years (42.7%), followed by those aged 22-23 years (24.7%). Over half of the sample was female (56.0%), and 42.0% was male. In terms of year level, we find a relatively consistent proportion of students participating from each stage in the 3rd and 4th years compared to first and second: First year (23.4%), 2nd (27.3%), 3rd year (24.8%), 4th/final year: Higher proportions are registered for the "other" category = 24.5%. Most of the participants studied in public schools (61.3%) and 38.7% in private colleges. Concerning previous experience with AI-style learning technologies, most reported a little (37.3%), followed by a little bit (32.0%). However, in most cases, students were reasonably aware of Artificial Intelligence-enabled learning aids. This kind of demographic characterization increases transparency in reporting sample characteristics and provides a frame of reference for understanding the study's findings.

The percentage of variance explained was 44% for workforce readiness, 34% for learning engagement, and 27% for Self-Efficacy, providing evidence of artificial intelligence-enabled learning's moderate explanatory contribution to the supported structure (Table 7).

The structural model indicated that realization of artificial intelligence-enabled learning has a positive, statistically significant direct effect on workforce readiness (β = 0.29, P < 0.001). In terms of standardized effect-size interpretations, such a coefficient is moderate (0.29) or strong (0.58). Artificial intelligence-enabled learning is also a strong predictor of learning engagement (β = 0.58, P < 0.001) and self-efficacy (β = 0.52, P < 0.001), indicating its impact on critical psychological mediators. Learning engagement (β = 0.31, P < 0.001) and self-efficacy (β = 0.36, P < 0.001) are both significant predictors of workforce readiness, suggesting partial mediation. These results support the theorized dual pathways and psychological processes through which Artificial Intelligence-enabled learning impacts work readiness.

Bootstrapping analysis with 5,000 resamples supported the mediation of learning engagement and self-efficacy in the relationship between artificial intelligence-enabled learning and workforce readiness (Table 8). The indirect effect through learning engagement (β = 0.18, P < 0.001) and through self-efficacy (β = 0.19, P < 0.001) represent meaningful mediation magnitudes, indicating that a substantial portion of the effect operates through psychological mechanisms rather than solely through direct pathways. The total indirect effect (β = 0.37) further confirms the robustness of the mediated structural model.

Table 9 presents the total effect of Artificial Intelligence-Enabled Learning (AIEL) on workforce readiness. The findings reveal that AIEL has a direct effect of 0.29 and an indirect effect of 0.37, resulting in a total effect of 0.66. These results indicate that AIEL exerts a substantial positive influence on workforce readiness both directly and indirectly through the mediating variables included in the structural model. The greater indirect effect further suggests that learning engagement and self-efficacy play significant roles in strengthening the relationship between AIEL and workforce readiness.

At the same time, the results suggest a high degree of integration of artificial intelligence–enabled learning within hospitality and tourism curricula, with an overall mean of 3.46 (Tables 10 and 11). Among the indicators, hands-on activities enhanced by artificial intelligence ranked highest, suggesting that most students appreciate hands-on and technology-aided learning. While personalized artificial intelligence learning content received the second-lowest mean score, it was still near the upper end of the very high range, indicating that tools based on Artificial Intelligence are overall seen as adequate instructional supports. On the whole, the findings reveal that Artificial Intelligence adoption is currently embedded in the teaching and learning activities of these institutions (Jaramillo et al., 2025).

The finding that learning engagement was high, with an average mean value of 3.36, confirmed the positive impact of artificial intelligence in instruction on students' participation, attention, and motivation. Participation in artificial intelligence-driven activities was rated highest, highlighting the engagement that structured, technology-based learning activities provided to maintain involvement (Table 12). Motivation for continued learning after

Table 7: Structural model results

Hypothesis	Structural path	Standardized β	SE	t-value	P-value	Decision
H_1	AIEL → Workforce Readiness	0.29	0.07	4.14	<0.001	Supported
H_2	AIEL → Learning Engagement	0.58	0.06	9.67	<0.001	Supported
H_3	AIEL → Self-Efficacy	0.52	0.06	8.74	<0.001	Supported
H_4	Learning Engagement → Workforce Readiness	0.31	0.08	3.88	<0.001	Supported
H_5	Self-Efficacy → Workforce Readiness	0.36	0.07	5.12	<0.001	Supported

AIEL: Artificial intelligence–enabled learning, SE: Self-efficacy

Table 8: Bootstrapping results for mediation analysis

Indirect path	Indirect effect (β)	Boot SE	95% CI lower	95% CI upper	P-value	Mediation type
AIEL → LE → WR	0.18	0.05	0.09	0.28	<0.001	Partial Mediation
AIEL → SE → WR	0.19	0.05	0.10	0.29	<0.001	Partial Mediation
Total Indirect Effect	0.37	0.06	0.25	0.49	<0.001	—

AIEL: Artificial intelligence–enabled learning, LE: Learning engagement, SE: Self-efficacy, WR: Workforce readiness

Table 9: Total effect summary

Path	Direct effect	Indirect effect	Total effect
Artificial intelligence–enabled learning → Workforce readiness	0.29	0.37	0.66

Table 10: Model fit indices

Fit Index	Recommended threshold	Model value	Interpretation
χ^2/df	<3.00	2.11	Acceptable
CFI	≥0.90	0.94	Good Fit
TLI	≥0.90	0.93	Good Fit
RMSEA	≤0.08	0.058	Acceptable
SRMR	≤0.08	0.049	Good Fit

CFI: Comparative fit index, TLI: Tucker-Lewis index, RMSEA: Root mean square error of approximation, SRMR: Standardized root mean square residual

Table 11: Artificial intelligence enabled learning

Item	Mean	SD	Verbal description
Artificial intelligence tools integrated in courses	3.48	0.52	Very High
Personalized artificial intelligence learning content	3.41	0.55	Very High
Artificial Intelligence assists understanding of concepts	3.44	0.50	Very High
Artificial intelligence enhanced hands on activities	3.52	0.49	Very High
Teachers' effective use of artificial intelligence	3.46	0.53	Very High
Overall mean	3.46	0.52	Very High

SD: Standard deviation

Table 12: Learning engagement

Item	Mean	SD	Verbal description
Artificial intelligence encourages class participation	3.39	0.56	Very high
Artificial intelligence improves attentiveness	3.34	0.58	Very high
Artificial intelligence motivates extra learning	3.28	0.60	High
Engagement in artificial intelligence enhanced activities	3.42	0.54	Very high
Artificial intelligence increases motivation in hospitality and tourism management courses	3.37	0.55	Very high
Overall mean	3.36	0.57	Very high

SD: Standard deviation

Table 13: Self-efficacy

Item	Mean	SD	Verbal description
Confidence using artificial intelligence platforms	3.31	0.59	Very high
Ability to learn artificial intelligence related tasks	3.38	0.56	Very high
Comfort with academic challenges	3.29	0.61	High
Ability to learn new technologies	3.43	0.53	Very high
Artificial intelligence increases career confidence	3.47	0.50	Very high
Overall mean	3.38	0.56	Very high

SD: Standard deviation

structured activities was lower but still high. These results imply that Artificial Intelligence integration enhances in-class commitment and structured academic involvement (Korayim et al., 2025).

Self-efficacy had an overall mean of 3.38, indicating that artificial intelligence-based learning environments increase students' confidence in their ability to complete academic and career-related tasks (Table 13). Relatively higher confidence was reported in artificial intelligence, particularly in leveraging it for career development, reflecting a more positive perception of being prepared. They had significantly less confidence in their ability to face academic challenges, yet their overall confidence remained high. This trend indicates that the introduction of Artificial Intelligence further increases perceived competence, but other academic supports could enhance resilience to difficult learning conditions (Zhang et al., 2025).

Skills in the digital employability category had a very high average rating of 3.40; thus, this mean score indicates that students felt confident in technology-related skills (Table 14). Scoring was highest for preparedness for technology-driven work and lowest, relatively, for the collaborative use of artificial intelligence tools. Results imply that students are individually competent in digital skills, whereas the cumulative level may require more instructional attention. These findings parallel studies that have illustrated the potential of technology-enhanced learning environments for developing digital competence and employability readiness at the individual level, but leveraging skill development collectively when using artificial intelligence in collaborative practices requires intentional pedagogical scaffolding (Zhao et al., 2025).

3.2. Workforce Readiness

Service communication expertise was reported at a high level, with a general mean of 3.42, suggesting a high perceived readiness for digital-mediated transactions with customers (Table 15). This result aligns with previous studies indicating that digital learning environments improve students' preparedness for technology-supported service communication and customer interaction in hospitality and tourism (Rather et al., 2026).

Table 14: Digital employability skills

Item	Mean	SD	Verbal Description
Familiarity with digital tools	3.44	0.51	Very high
Critical assessment using artificial intelligence	3.35	0.55	Very high
Digital problem-solving skills	3.39	0.54	Very high
Collaboration on artificial intelligence platforms	3.32	0.58	Very high
Readiness for tech related jobs	3.48	0.49	Very high
Overall mean	3.40	0.53	Very high

SD: Standard deviation

Table 15: E.1 service communication competence

Item	Mean	SD	Description
Digital customer communication	3.42	0.52	Very high
Tech based customer service	3.39	0.55	Very high
Improved professional communication	3.45	0.50	Very high
Overall mean	3.42	0.52	Very high

SD: Standard deviation

The overall mean of 3.36 in the summary sheet indicates a high level of perceived problem-solving skills among students exposed to artificial intelligence-enabled learning (Table 16). Students reported high confidence in using digital processes and artificial intelligence-enabled systems to analyze service-based problems and inform decisions. The highest mean score was for the belief that artificial intelligence enhances practice-based decision-making, indicating the potential of artificial intelligence-enabled learning to develop analytical and applied decision-making skills. These results suggest that Artificial Intelligence-enabled learning enhances cognitive competence in hospitality and tourism learning environments.

The overall mean of 3.46 indicates a very high level of readiness to function within technology-oriented work environments (Table 17). Although students had high levels of confidence in learning digital workplace systems, they also reported ease and familiarity with technology-mediated service operations. The highest score was observed for artificial intelligence, which helps improve work readiness, suggesting that using artificial intelligence to teach will better align academic preparation with current industry practice. These findings further demonstrate the need for Artificial Intelligence-enabled learning to prepare students for digitally integrated work environments (Le et al., 2025).

Digital capability was highly valued, with an overall mean of 3.44, as artificial intelligence-enabled learning enhanced technology-specific professional expertise (Table 18). This result aligns with previous research that found that artificial intelligence-enabled learning develops digital competences and technology-related professional skills necessary in the contemporary service economy (Max et al., 2022).

The artificial intelligence teaching model was widely accepted, with an overall mean of 3.48, confirming students' positive attitudes toward structured integration of artificial intelligence across the hospitality and tourism curriculum (Table 19). The time for integrating the curriculum is at readiness levels where it can be systematically launched, not locally adopted. These findings reinforce the institutionalization of artificial intelligence-enabled learning approaches in curricula (Islam et al., 2026).

Table 16: E.2 problem-solving ability

Item	Mean	SD	Description
Use of digital tools to solve problems	3.36	0.56	Very high
Decision making using artificial intelligence	3.33	0.58	Very high
Artificial intelligence improves real service problem solving	3.40	0.53	Very high
Overall mean	3.36	0.56	Very high

Table 17: E.3 fit in technology-oriented work environments

Item	Mean	SD	Description
Readiness for tech driven workplaces	3.47	0.50	Very high
Fluency with workplace technologies	3.41	0.53	Very high
Artificial intelligence learning improves work readiness	3.49	0.49	Very high
Overall mean	3.46	0.51	Very high

Table 18: E.4 digital competence

Item	Mean	SD	Description
Strong digital skills	3.38	0.55	Very high
Comfort with tech related tasks	3.44	0.51	Very high
Artificial Intelligence enhances overall digital competence	3.50	0.48	Very high
Overall mean	3.44	0.51	Very high

Table 19: F. Artificial intelligence teaching model

Item	Mean	SD	Description
Artificial intelligence integration in curriculum	3.51	0.49	Very high
Artificial intelligence prepares students for labor market	3.47	0.50	Very high
Blended artificial intelligence traditional learning	3.43	0.52	Very high
Artificial intelligence across hospitality and tourism management curricula	3.49	0.48	Very high
Overall mean	3.48	0.50	Very high

3.3. Theoretical Implication

The results support social cognitive theory and engagement theory, and identify learning engagement and self-efficacy as the psychological processes through which seven-stage artificial intelligence-enabled learning connects with workforce readiness. The mediating model, which is also empirically substantiated, elucidates the mechanism by which artificial intelligence-enabled learning environments influence the development of professional competence. It provides theoretical generalizability to existing studies that were more focused on technology acceptance or higher education contexts by embedding the analysis within hospitality and tourism education in an emerging market.

3.4. Practical Implication

The implications for higher educational institutions offering hospitality and tourism studies are vital based on this study's results. First, educational institutions must strategically incorporate artificial intelligence-enabled learning tools into curriculum design to optimize student engagement and foster confidence in adaptive professional skills. The strong mediating effects of learning engagement and self-efficacy indicate that artificial intelligence integration should not focus solely on technology but be pedagogically grounded (Le et al., 2026).

Second, teachers need to adopt artificial intelligence-enabled learning, adaptive learning solutions, and intelligent feedback systems to bridge the gap between classroom training and industrial practice (Colliot et al., 2024). Institutions can prepare graduates for the dynamic context of technology-rich hospitality sectors by enhancing psychological readiness factors, such as self-efficacy.

Policy makers and university administrators may meanwhile use these results to focus investments in artificial intelligence-enabled educational infrastructure and faculty development programs (Hemachandran et al., 2022).

3.5. Limitations of the Study

Several limitations in this analysis need to be addressed. First, the cross-sectional nature of this study precludes causal inferences among the constructs. Prospective research may benefit from adopting longitudinal designs to capture developmental effects better. Second, although several institutions were represented, the study was conducted in a defined geographical context within the Philippines, and its replicability in other national or institutional contexts is uncertain. Third, participation was voluntary, and the potential for self-selection bias could not be excluded entirely, such as the possibility that students who favored artificial intelligence-enabled learning were more likely to participate in this survey. Furthermore, variations in students' prior exposure to artificial intelligence tools across institutions could have tempered the effectiveness of perception-based assessment. Finally, reliance on self-report measures may have inflated estimates of self-efficacy and workforce readiness by leading participants to overestimate their actual performance relative to objective performance-based assessments.

4. CONCLUSION AND RECOMMENDATION

4.1. Conclusion

The current paper aimed to investigate the impact of artificial intelligence-enabled learning on work readiness among hospitality and tourism students. The mediating roles of learning engagement and self-efficacy were examined. The findings reveal that artificial intelligence-enabled learning may have a strong potential to enhance the direct and indirect effects on workforce readiness, particularly by enriching students' engagement and confidence.

The empirical evidence for a mediated structural model underscores the importance of incorporating pedagogically robust artificial intelligence technologies in hospitality and tourism education. The results provide evidence that the psychological aspects of active learning and self-efficacy are part of workforce preparedness, not just technical skills.

Given that the lens of artificial intelligence is increasingly shaping service-dominated sectors, pipeline education for hospitality and tourism industries will require more than adopting technology; it will require integrating evidence-based pedagogy, framed around psychological readiness for change and job-readiness capabilities. Higher education institutions should integrate artificial intelligence-supporting learning approaches that encourage the engagement of process, self-efficacy-building, and digital literacy into general digital fitness for continuous transition to the digital era of economies worldwide.

The study offers theoretical, methodological, and contextual implications for the literature on artificial intelligence-enabled learning in hospitality and tourism education. Theoretically, it offers a mediated model that explains how learning engagement and self-efficacy mediate the relationship between artificial intelligence-enabled learning and workforce readiness. Methodologically, it confirms a covariance-based structural equation model in an emerging-market context and, in turn, bolsters the empirical rigor of employability-related research. At the outset, it adds evidence from the Philippines, where the literature has mainly been confined to Western contexts. It advances global knowledge on technology-supported curriculum change in service industries.

4.2. Recommendation

1. Future research may adopt retrospective, experimental, or mixed-methods designs to examine how workforce readiness develops as exposure to Artificial Intelligence-enabled learning evolves over time. Analytical models could also test the roles of engagement and self-efficacy as mediators in explaining the impact of Artificial Intelligence-enabled learning on employability. In light of the relatively weak findings on personalization, independent learning, and collaborative digital engagement, future research can examine the instructional designs and Artificial Intelligence capabilities that specifically target these factors by adding performance-based indicators to support perception-based measures.
2. Ongoing embedding of artificial intelligence-enabled learning within hospitality and tourism education is desirable to uphold and enhance the observed high levels of work readiness. Attention should then be given to equitable access to digital learning environments, the responsible and ethical use of artificial intelligence, and ensuring that student outcomes are better aligned with the competencies demanded by technology-based service industries. Targeted support for exposure to workplace-related technology is significant, as more experience with operational systems may also develop digital employment skills.
3. At the institutional level, the organized delivery of artificial intelligence-enabled learning is suggested through interrelated pedagogies that support personalized, self-directed, and participatory study. Although the results were already awe-inspiring in terms of engagement and self-efficacy, it would be interesting to see whether further supports, such as adaptive learning pathways, scaffolded academic challenges, and collaborative project-based tasks, could address the lower dimensions identified. Explicit guidance on how artificial intelligence can be used pedagogically could help ensure consistent, highly effective integration across learning landscapes.
4. These are industry-partnered learning experiences that build understanding of the application of artificial intelligence-enabled learning in genuine professional settings. By including authentic service situations, technology-assisted problem-solving, and practice tasks, students' confidence in using workplace technologies can be increased, and the transfer of academic learning to work contexts can be strengthened. For practical skills, such alignment helps create opportunities to develop these competencies, which align with the high readiness found in the study.
5. Curricular sections may benefit from systematic integration of artificial intelligence-enabled learning across subject domains rather than isolated implementation within specific courses. Experience- and problem-based, collaborative learning designs aided by AI tools may help enhance students' basic digital competencies. Formal opportunities for independent and team-based learning could better prepare students to work in complex, technology-saturated environments.
6. Artificial intelligence-enabled learning systems need to develop further to enable adaptive, collaborative, and context-driven learning. User-centric design, open feedback loops, and context-based learning situations in the hospitality and tourism industries could also enhance learner confidence, motivation, engagement, and, consequently, competence. When system functions are coordinated with the learning requirements

articulated in this study, workforce readiness can be more sustained and preparedness-focused.

REFERENCES

Alam, S.S., Masukujjaman, M., Makhbul, Z.K.M., Ali, M.H., Ahmad, I., Mamun, A.A. (2023), Experience, Trust, eWOM engagement and usage Intention of AI enabled services in hospitality and tourism industry: Moderating mediating analysis. Journal of Quality Assurance in Hospitality and Tourism, 25(6), 1635-1663.

Baluyut, P. (2025), Bridging the gap: Preparing students for the real world of tourism and hospitality management at state universities. International Journal on Culture History and Religion, 7(SI3), 225-238.

Bandura, A. (1997). Self-efficacy: The exercise of control. W. H. Freeman and Company.

Cheung, K.S., Geertshuis, S., Liu, Q., Albashiry, N. (2025), A systematic curriculum intervention: Embedding employability through constructive alignment to enhance student learning. The Curriculum Journal, 37, 465-483.

Colliot, T., Krichen, O., Girard, N., Anquetil, É., Jamet, É. (2024), What makes tablet-based learning effective? A study of the role of real-time adaptive feedback. British Journal of Educational Technology, 55(5), 2278-2295.

De Guzman, A., Bollozos, J.K., De Los Santos, L., Monton, E.M., Selosa, A.K. (2020), Genuineness matters in tourism: A phenomenology of filipino travel management students' emotional experiences of tour guides' verbalized hospitality during destination immersion. Journal of Quality Assurance in Hospitality and Tourism, 22(3), 267-292.

Elshaer, I.A., Azazz, A.M.S., Mohammad, A.A.A., Fayyad, S. (2025), Decoding success: The role of E-Learning readiness in linking technological skills and employability in hospitality management graduates. Information, 16(1), 47.

Fredricks, J. A., Blumenfeld, P. C., & Paris, A. H. (2004). School engagement: Potential of the concept, state of the evidence. Review of Educational Research, 74(1), 59–109.

Goecke, B., Weiss, S., Barbot, B. (2025), Content validity of creativity self-report questionnaires from PISA 2022. The Journal of Creative Behavior, 59(2), 70026.

Gu, H., Chon, K., Song, X., Xie, X. (2026), AI for tourism and hospitality education in China: Policies, challenges and prospect. Journal of Teaching in Travel and Tourism, 26, 1-16.

Hafeez, M.H., Kokash, H.A., Ahsan, M.N., Tariq, B., Alam, S.S. (2026), Organizational and external e-readiness, AI adoption in hospitality industry: Empirical study. Journal of Quality Assurance in Hospitality and Tourism, 2026, 1-25.

Hemachandran, K., Verma, P., Pareek, P., Arora, N., Kumar, K.V.R., Ahanger, T.A., Pise, A.A., Ratna, R. (2022), Artificial intelligence: A universal virtual tool to augment tutoring in higher education. Computational Intelligence and Neuroscience, 2022, 1410448.

Islam, M.T., Kumar, J., Konar, R., Amin, M., Ragavan, N.A., Cobanoglu, C. (2026), The friend-foe paradox of ChatGPT in hospitality and tourism education: A systematic literature review and future research directions. Journal of Teaching in Travel and Tourism, 2026, 1-28.

Jaramillo, M., Baquiran, C., Madayag, C., Alih, C., Manera, A., Ramones, J. (2025), Exploring the Integration of Artificial intelligence in Filipino language Education: Enhancing teaching practices and learning outcomes in higher education institutions. International Journal on Culture History and Religion, 7(SI3), 416-431.

Kahu, E. R. (2013). Framing student engagement in higher education. Studies in Higher Education, 38(5), 758–773.

Kong, W., Hu, H., Wang, Z., Qiao, J., Liu, J. (2025), The double-edged sword effect of generative AI adoption on students' sustainable entrepreneurship intentions. Behavioral Sciences, 15(12), 1705.

Korayim, D., Bodhi, R., Badghish, S., Yaqub, M.Z., Bianco, R. (2025), Do generative artificial intelligence related competencies, attitudes and experiences affect employee outcomes? An intellectual capital perspective. Journal of Intellectual Capital, 26(3), 596–615.

Laundon, M., McDonald, P., Greentree, J. (2023), How education and training systems can support a digitally-enabled workforce for the manufacturing industry of the future: An exploratory study. Education + Training, 65(6/7), 909-922.

Le, H., Shen, Y., Li, Z., Xia, M., Tang, L., Li, X., Jia, J., Wang, Q., Gašević, D., Fan, Y. (2025), Breaking human dominance: Investigating learners' preferences for learning feedback from generative AI and human tutors. British Journal of Educational Technology, 56(5), 1758-1783.

Le, T.H., Huynh, L., Dang, B., Pham, H., Nguyen, N.T.V., Nguyen, A. (2026), Development and evaluation of artificial intelligence literacy training for teacher education students. British Journal of Educational Technology, 56, 1-32.

Liu, X., Zhang, X., Dang, Y., Gao, W. (2023), Career education skills and career adaptability among college students in China: The mediating role of career decision-making self-efficacy. Behavioral Sciences, 13(9), 780.

Max, A., Lukas, S., Weitzel, H. (2022), The relationship between self-assessment and performance in learning TPACK: Are self-assessments a good way to support preservice teachers' learning? Journal of Computer Assisted Learning, 38(4), 1160-1172.

Mughal, M.F., Cai, S., Faraz, N.A., Haiying, C., Poulova, P. (2024), Green servant leadership and employees' workplace green behavior: Interplay of green self-efficacy, green work engagement, and environmental passion. Current Psychology, 43, 26806-26822.

Nguyen, D.M., Chiu, Y.H. (2023), Corporate social responsibility authenticity as an antecedent to customer citizenship behavior: Evidence from hospitality industry in Taiwan. Journal of Hospitality Marketing and Management, 32(4), 477-504.

Rather, R.A., Rasul, T., Ladeira, W.J., De Oliveira Santini, F., Ramkissoon, H. (2026), Artificial intelligence (AI) in tourism, hospitality, and service research: A new digital frontier for consumer engagement, psychology, and behavior. Journal of Hospitality Marketing and Management, 2026, 1-18.

Singh, A., Singh, H.P., Alam, M.F. (2025), The impact of AI tools enabled student engagement on academic performance, employability, and empowerment in Ha'il Region, Saudi Arabia. Acta Psychologica, 262, 106103.

Šulc, A., Erčulj, V., Mihelič, A. (2025), Translation symmetry and familiarity of end-point anchor points in Likert scales. Methodology, 21(3), 161-178.

Wan, P., Gu, X. (2025), Designing an integrated concept mapping and generative AI approach to develop pre-service teachers' digital storytelling project outcomes and critical thinking. British Educational Research Journal, 52, 1313-1338.

Wut, T.M., Chan, E.A., Wong, H.S., Chan, J.K.Y. (2025), Perceived artificial intelligence literacy and employability of university students. Education + Training, 67(2), 258-274.

Zhang, B., Li, W., Jou, M. (2025), The influence of generative artificial intelligence support on learning anxiety and academic expectation stress: The mediating role of self-efficacy. Interactive Learning Environments, 2025, 1-17.

Zhao, Y., Xu, Y., Long, T. (2025), Understanding pre-service science teachers' collaborative discourse patterns in a GENAI integrated collective reflection: A network analytic approach. Journal of Science Education and Technology, 35, 141-159.