The Relationships among Technological Innovation, AI Self-efficacy, Learning Anxiety, Literacy, and Usage Satisfaction: An Empirical Study Based on Chinese Vocational College Students

Li Liao and Jian-Hong Ye *

Faculty of Education, Beijing Normal University, Beijing, China
Email: 202321010097@mail.bnu.edu.cn or 18774882682@163.com (L.L.);
kimpo30107@hotmail.com or jianhong.ye@bnu.edu.cn (J.-H.Y.)
*Corresponding author
Manuscript received October 9, 2025; revised November 27, 2025; accepted January 26, 2026; published July 13, 2026

***Abstract*—Artificial Intelligence (AI) is being rapidly integrated into education, and is demonstrating its transformative potential. However, its widespread adoption introduces psychological challenges that can amplify or diminish its benefits. Grounded in the Technology Readiness Index and Person-Process-Technology framework, this study explored the intrinsic relationships among vocational college students' technological innovation, AI self-efficacy, learning anxiety, literacy, and usage satisfaction. Addressing the gap in validated psychological responses, a cross-sectional survey was conducted among 647 Chinese vocational students (mean age: 19.50) using a 32-item 5-point Likert scale. The instrument demonstrated robust reliability with Cronbach's α coefficients ranging from 0.840 to 0.923. Structural Equation Modeling results indicated that technological innovation significantly predicted AI self-efficacy (β = 0.678, p < 0.001) and reduced anxiety (β = −0.332, p < 0.001). AI self-efficacy ((β = 0.561, p < 0.001) and anxiety (β = −0.230, p < 0.001) significantly influenced AI literacy (β = 0.490), which strongly predicted usage satisfaction (β = 0.607, p < 0.001). In conclusion, the significant influence of psychological factors on literacy confirms that psychological readiness is a prerequisite for technical success. Regarding further uses, this study validates a reliable assessment tool for educators and suggests that vocational colleges should move beyond mere technical training to implement curricula that enhance self-efficacy and mitigate anxiety, empirically boosting students' AI acceptance.**

***Keywords*—Artificial Intelligence (AI), AI self-efficacy, AI learning anxiety, AI literacy, AI usage satisfaction, Technology Readiness Index (TRI), People-Process-Technology (PPT)**

I. Introduction

Artificial Intelligence (AI) technology is being integrated into the education sector at an unprecedented pace, and is demonstrating its immense transformative potential [1]. In vocational education, AI tools accelerate and refine skill training through adaptive learning pathways, virtual training scenarios, and instant feedback [2]. However, the rapid iteration and widespread adoption of AI technologies also bring new psychological challenges that can amplify or diminish the benefits of the technology [3]. For instance, while technological innovation acts as a core driver for adopting emerging technologies [4], its excessive development in practice-oriented vocational settings may lead students to prioritize technological shortcuts over solidifying foundational skills [5]. Furthermore, the lack of transparency in AI operations often causes anxiety [6], fueling concerns about being "replaced" or being unable to discern accuracy, thus creating a new form of learning anxiety [7]. Consequently, AI usage satisfaction depends not only on students' confidence, or on their AI self-efficacy to efficiently complete tasks [8, 9], but also on their AI literacy, which is increasingly regarded as an indispensable competency for navigating the AI-driven world [10, 11]. Therefore, understanding how these psychological variables interact to influence students' perceptions of technology quality is pivotal [12, 13].

Despite the significance of these factors, there is little systematic empirical research on how students in vocational education—an educational setting emphasizing technical application and practical skill development—form actual satisfaction with AI tools amid the interplay of these key psychological variables [14]. While recent research has begun to uncover correlations among variables such as technological innovation, AI self-efficacy, AI learning anxiety, AI literacy, and AI usage satisfaction [15, 16], the precise relationships and interactive mechanisms among them remain unclear. Researchers are striving to understand causal relationships [17], yet a comprehensive understanding of the specific variables influencing the vocational AI domain is currently lacking.

To address this research gap, this study aimed to explore the associations among technological innovation, AI self-efficacy, AI learning anxiety, AI literacy, and AI usage satisfaction among students in Chinese vocational colleges. To achieve this, we adopted the Technology Readiness Index (TRI) and the People-Process-Technology (PPT) framework as theoretical lenses. The TRI identifies dimensions such as Optimism and Innovativeness as motivators, and Discomfort and Insecurity as barriers, effectively predicting willingness to use intelligent systems [18–20]. Concurrently, the PPT framework emphasizes that successful application depends on the synergistic alignment of "human" capabilities, "process" interaction methods, and "technology" functionality [21]. Given their combined effectiveness in terms of interpreting acceptance and usage behavior [22], these models provide the theoretical structure to explain the relational mechanisms in our study.

The findings of this study offer significant theoretical and practical contributions. Theoretically, the results not only enhance the understanding of the TRI model's broader applicability beyond technology usability, but also provide a comprehensive explanation for factors related to people,

doi: 10.18178/ijiet.2026.16.7.2636

processes, and technology. Practically, these results help researchers and educators gain deeper insights into the relationship between students' positive interactions with AI and their AI learning anxiety. This facilitates the development of targeted strategies to mitigate the negative impacts of AI application, ensuring that vocational colleges can better address students' varying levels of technological readiness during AI integration.

II. Theory and Hypotheses

A. Theoretical Models

1) Technology Readiness Index (TRI)

The TRI reflects an individual's propensity to adopt innovative technological products or services, aiming to measure willingness to accept and use new technologies [18]. TRI assesses technological readiness by evaluating four key personality traits: optimism, innovativeness, discomfort, and insecurity. Optimism and innovativeness serve as motivating factors, encouraging active acceptance and use of new technologies, whereas discomfort and insecurity act as barriers, reducing the likelihood of adoption [23]. Since its development, the TRI theoretical model has been extensively applied to study the acceptance and adoption of new technologies, products, platforms, and service models, demonstrating broad applicability and predictive power [24]. While general acceptance models predict usage, TRI is particularly necessary for this study as it uncovers the specific paradoxical psychological states—coexisting enthusiasm and anxiety—that users experience when facing emerging AI tools.

The TRI theoretical model has been applied to investigate students' attitudes toward technology across different countries. For instance, Zhao *et al*. [25] identified key factors influencing Chinese university students' willingness to use and satisfaction with AI tools such as ChatGPT. Other scholar have explored the maturity levels of vocational students in Indonesia regarding mastering digital technologies for learning [26]. Shakeel *et al*. [27] examined Bangladeshi vocational students' readiness for blended learning and attitudes toward online learning, while Moca and Badulesc [28] investigated how external factors such as learning autonomy and AI self-efficacy influence students' willingness to adopt and use mobile devices. In this current research, TRI complements the structural approach by providing a micro-theoretical lens to decode the "People" dimension. It specifically explains how the external stimulus of technology triggers two distinct, competing psychological paths—motivators (AI efficacy) versus barriers (AI anxiety)—thereby enriching the analysis of student adoption mechanisms beyond simple behavioral usage.

2) People-Process-Technology (PPT)

Integrating AI into vocational education requires a systemic perspective. The PPT framework, rooted in socio-technical systems theory, emphasizes that effective system operation depends on the dynamic equilibrium of three elements: personnel (People), processes (Process), and technology (Technology) [29]. After evolving through business process management concepts [30, 31], this framework gained widespread application in information systems, particularly establishing consensus in cybersecurity [32, 33] and knowledge management research.

This study utilized PPT as the necessary macro-structural framework to organize the causal path of AI adoption, which was then deepened by TRI's psychological insights. The Technology dimension was operationalized as Technological innovation, serving as the external trigger [34]. The People dimension was investigated through the lens of TRI, focusing on the internal cognitive conflict between AI self-efficacy (motivator) and AI learning anxiety (barrier) [35]. The Process dimension reflects the capability required for implementation, represented here as AI literacy [36]. These elements dynamically interact to influence the final outcome: usage satisfaction. By embedding TRI within the PPT structure, this study rigorously connected the external technological environment to internal psychological states, explaining how these jointly determine the "Process" (literacy) and "Outcome" (satisfaction). This integration fills an empirical gap by demonstrating that successful AI adoption depends not just on technology availability, but also on alignment between users' psychological readiness (People) and their operational capabilities (Process).

B. Research Hypotheses

1) The relationships between technological innovation, AI self-efficacy, and AI learning anxiety

Technological innovation refers to an individual's ideological inclination toward becoming a technology pioneer; such individuals are typically early adopters and active explorers of new technologies [18]. Highly technologically innovative individuals, driven by their exploratory spirit and strong motivation to master new technologies, proactively seek AI-related knowledge, invest greater cognitive resources, and readily engage in practical operations [37]. According to Bandura's social cognitive theory, learners experience heightened self-efficacy when achieving personal success [38]. Consequently, highly technologically innovative individuals significantly reinforce their belief that "I can understand and apply AI" through repeatedly solving AI technical problems [39, 40].

AI learning anxiety refers to a negative emotional state of tension, unease, or even fear when confronting AI technology [41]. Its essence corresponds to two barrier dimensions within TRI: "discomfort" and "insecurity." Discomfort stems from frustration arising when individuals feel unable to effectively control the technology, while insecurity originates from concerns about technological reliability and privacy issues [37]. Individuals possessing high levels of technological innovation perceive learning AI as an exciting challenge and opportunity rather than as a threat. They typically maintain more open and optimistic trust in technology, enabling them to remain patient and resilient when encountering difficulties, viewing obstacles as temporary and surmountable problems [15]. This partially mitigates excessive concerns about the uncertainties and potential risks of AI learning (AI learning anxiety). Therefore, we proposed the following hypotheses:

H1: Technological Innovation positively correlates with AI self-efficacy.

H2: Technological Innovation negatively correlates with AI learning anxiety.

2) *The relationships between AI self-efficacy, AI learning anxiety, and AI literacy*

From the TRI perspective, AI learning anxiety corresponds to the "insecurity" dimension, manifesting as heightened concerns and risk perception regarding new technologies. AI self-efficacy, meanwhile, reflects an individual's confidence in their ability to master new technologies, aligning with the motivational factors of "optimism" and "innovation" [18]. When individuals possess high levels of AI self-efficacy, their perceived control over AI technology increases, reducing insecurity stemming from uncertainty or anticipated failure. This significantly diminishes AI learning anxiety [42]. TRI emphasizes that "optimism" and "innovation" as drivers of technology adoption translate into proactive learning engagement and exploratory behavior. Individuals with high AI self-efficacy are more inclined to proactively seek information, experiment with new features, and accumulate knowledge, skills, and experience through sustained practice, thereby enhancing their AI literacy. Conversely, those with low self-efficacy may avoid deep learning due to the dual barriers of discomfort and insecurity, limiting their AI literacy growth [43]. Therefore, we proposed the following hypotheses:

H3: AI self-efficacy is negatively correlated with AI learning anxiety.

H4: AI self-efficacy is positively correlated with AI literacy.

3) *The relationship between AI learning anxiety and AI literacy*

Previous studies have confirmed that the less comprehensive people's understanding of AI is, the poorer their usage skills and basic judgment become, and the greater their intimidation and anxiety regarding AI learning [44]. When learners perceive themselves as lacking foundational, reliable AI literacy, and struggle to interact fluently with AI, this reinforces their apprehension of AI, thereby amplifying their AI learning anxiety [45]. Learners with higher AI literacy demonstrate greater confidence in embracing AI challenges and leveraging AI to enhance research efficiency and innovation, and exhibit lower AI learning anxiety. Therefore, we proposed the following hypothesis:

H5: AI learning anxiety is negatively correlated with AI literacy.

4) *The relationship between AI literacy and AI usage satisfaction*

AI literacy plays a crucial role in today's digital environment, influencing whether learners choose to leverage AI technologies to support their learning activities. Learners possessing high levels of AI skills can effectively utilize these technologies for tasks such as data collection, organization, and literature translation. This not only reduces repetitive and labor-intensive tasks in the learning process, but also frees up more energy and time for engaging in more challenging and innovative research work [46]. Learners with AI literacy typically derive greater direct benefits from the technology, enhancing their satisfaction with AI usage [47]. Therefore, we anticipated that higher levels of AI literacy would promote learners' willingness to use AI and increase their satisfaction, hypothesized as follows:

H6: AI literacy positively correlates with AI usage satisfaction.

C. *Hypothesis Model*

We constructed a research model for AI innovative usage experiences based on the dual theoretical perspectives of the TRI and PPT frameworks, proposing six corresponding research hypotheses. The model aimed to systematically explore the intrinsic relationships among five core variables: technological innovation, AI self-efficacy, AI learning anxiety, AI literacy, and AI usage satisfaction. It sought to reveal individuals' psychological responses during the acceptance and usage of AI technologies. The specific research framework is illustrated in Fig. 1.

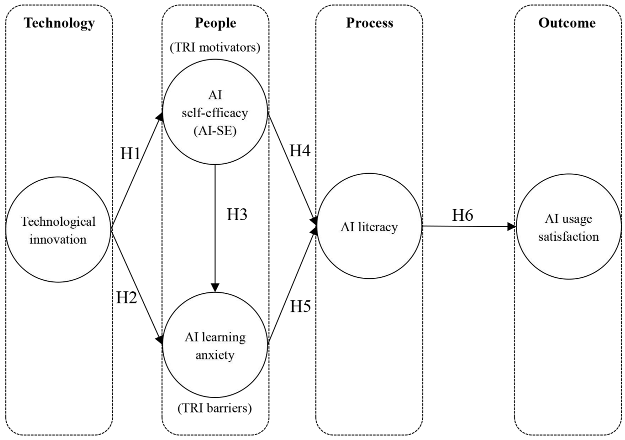

Fig. 1. Conceptual framework illustrating the hypothesized relationships among technological innovation, AI self-efficacy, AI learning anxiety, AI literacy, and AI usage satisfaction.

III. Research Design

A. *Procedure*

This study employed a cross-sectional research design using an online questionnaire. Data collection was conducted from September 1 to 19, 2025. The survey was distributed to students in Chinese vocational colleges via online platforms (Google Forms).

Regarding ethical considerations, while formal Institutional Review Board (IRB) approval was not mandatory under Chinese regulations for non-interventional social science research, the study adhered strictly to the Declaration of Helsinki. An informed consent statement was presented on the first page to verify eligibility (currently enrolled students) and explicitly inform participants of their right to withdraw at any time without penalty. To ensure data protection, all responses were anonymized, stored on encrypted devices, and accessible only to the research team.

B. *Participants*

A total of 712 questionnaires were initially collected. To ensure data reliability, inclusion and exclusion criteria were strictly applied. The study specifically recruited students currently enrolled in Chinese vocational colleges, encompassing both Higher Vocational and Vocational Undergraduate programs. Rigorous screening eliminated invalid entries, such as those completed in under 120 s or exhibiting overly consistent response patterns. Consequently, 65 invalid responses were removed, yielding a final valid sample of 647 participants (effective response rate: 90.87%; mean age: 19.50 years, *SD* = 1.32). Detailed demographic characteristics are presented in Table 1.

Regarding sampling strategy and representativeness, although convenience sampling was utilized, measures were taken to mitigate selection bias. The survey was distributed across multiple distinct vocational institutions to prevent data clustering. Furthermore, as shown in Table 1, the sample demonstrates significant diversity in terms of institutional affiliation (covering both public and private schools) and educational stages, which broadly aligns with the structural composition of China's vocational education sector, thereby enhancing the study's validity and representativeness.

Table 1. Demographic Information

Variable	*N*	%
Gender	Male: 367	56.7%
	Female: 280	43.3%
Educational Stage	Vocational High School: 352	54.4%
	Vocational Undergraduate: 295	45.6%
School Affiliation	Public schools: 405	62.6%
	Private schools: 242	37.4%
Usage Experience	Within six months: 92	14.2%
	Six months to one year: 282	43.6%
	Over one year: 273	42.2%
Primary Uses of AI Tools	Support academic studies: 225	34.8%
	Expand extracurricular knowledge: 242	17.4%
	Look up lifestyle information: 180	27.8%

C. Measures

All questionnaires in this study were self-administered and evaluated using a 5-point Likert scale, where 1 to 5 represented varying degrees of disagreement to agreement. The instrument included six background variable questions and 38 initial items across five scales.

To ensure robust validity, particularly for the newly adapted scales, a rigorous development process was followed. First, items were operationally defined based on established literature to ensure theoretical grounding. Second, the initial questionnaire was reviewed by three educational technology experts to verify its content validity, ensuring the completeness of constructs and logical structure. Third, to assess face validity, a pilot test was conducted with 12 students majoring in Vocational and Technical Education. These participants evaluated the items for difficulty and readability, and minor wording adjustments were made based on their feedback to ensure clarity for the target population.

1) Technological innovation

In this study, technological innovation refers to an individual's ideological inclination to act as a technology pioneer and active explorer who perceives AI learning as an exciting challenge rather than a threat. We referenced and revised the Consumer Innovation Scale developed by Hong *et al*. [48], comprising six items designed to measure participants' propensity to understand and adopt new technological products within specific domains. Sample items include: "In my social circle, I am usually the first to use new technological products" and "I know more about the latest technological products than others."

2) AI Self-Efficacy (AI-SE)

In this study, AI Self-Efficacy (AI-SE) refers to the specific belief held by an individual that I can understand and apply AI. We adapted the ChatGPT Self-Efficacy (ChatGPT-SE) scale from Lin *et al*. [49]. All items use a 5-point Likert scale, comprising six questions to measure participants' confidence and perceived competence in using AI to complete specific tasks or scenarios. Sample items include: "When AI outputs unsatisfactory results, I know how to quickly adjust instructions" and "I feel confident handling unexpected issues with AI applications."

3) AI learning anxiety

In this study, AI learning anxiety is defined as a psychological barrier manifesting as heightened apprehension and risk perception regarding the uncertainty of mastering AI technologies. We adapted the AI Learning Anxiety Scale from Li and Huang [50], comprising six items to measure participants' anxiety stemming from perceived difficulties in learning AI technologies. Sample items include: "I worry I won't be able to master AI applications" and "I lack confidence in learning AI applications." Higher average scores indicate greater tendency toward anxiety about learning AI tasks.

4) AI literacy

In this study, AI literacy refers to the comprehensive capability to possess the knowledge, skills, and judgment necessary to interact fluently with AI and leverage it for efficient learning and innovation. A scale based on the concept of AI literacy was developed for this study, comprising 12 items to measure participants' cognitive awareness regarding understanding, application capabilities, and related ethical considerations of AI technologies. Sample items include: "I am aware of the ethical issues AI may raise." Higher average scores on this variable indicated a higher level of AI literacy among participants.

5) AI usage satisfaction

In this study, AI usage satisfaction is defined as the positive gratification learners derive from the direct benefits of AI utilization. We adapted the ChatGPT Positive Experience Scale from Ye *et al*. [1], comprising eight items to measure participants' perceived positive impacts of AI usage. Sample items include: "I find AI feedback to be timely" and "I find AI responses to questions to be fluent." Higher average scores on this variable indicated greater positive experiences and satisfaction since participants began using AI.

D. Data Analysis Strategy

Structural Equation Modeling (SEM) is a multivariate data analysis method used to examine complex relationships between latent constructs and observed indicators [51]. This approach is widely employed in psychology and other social sciences to test substantive hypotheses [52]. Multiple developments in SEM have enhanced its utility across diverse data types, research designs, research questions, and contexts, with one core purpose being the assessment of theoretical relationships [53]. Consistent with these principles, this study employed SPSS 28.0 and the SEM-based AMOS 26.0 software to validate the research model using a systematic two-stage analytical strategy [54].

The analysis proceeded in three phases. First, data screening was conducted, employing Harman's single-factor test to assess potential Common Method Variance (CMV) [55]. Second, the measurement model was assessed via Confirmatory Factor Analysis (CFA). This phase included item analysis, where indicators with standardized factor loadings below 0.50 were considered for removal, as well as the evaluation of reliability (Cronbach's α, CR) and convergent validity (AVE). To strictly verify discriminant validity, the Heterotrait-Monotrait ratio (HTMT) criterion [56] was utilized alongside traditional metrics. Finally, the structural model was analyzed to estimate the causal relationships between exogenous and endogenous latent variables.

IV. RESULTS

The initial instrument consisted of 38 items measuring five constructs: Technological Innovation (6 items), AI Self-Efficacy (6 items), AI Learning Anxiety (6 items), AI Literacy (12 items), and AI Usage Satisfaction (8 items).

Prior to hypothesis testing, a rigorous item purification process was conducted. Through the Assessment of Common Method Variance (CMV) and Confirmatory Factor Analysis (CFA), items exhibiting low factor loadings or significant cross-loadings were removed to satisfy validity requirements (Table A1 in Appendix). Consequently, 6 items were excluded: 1 from Technological Innovation, 3 from AI Literacy, and 2 from AI Usage Satisfaction. The final Structural Equation Modeling (SEM) was conducted using the remaining 32 items.The specific results are as follows.

A. Measurement Model Assessment

Prior to conducting the final Confirmatory Factor Analysis (CFA), a preliminary item purification process was executed to ensure construct validity. Items exhibiting Standardized Factor Loadings (FL) below 0.50 were identified as having insufficient convergent validity and were consequently removed. The detailed list of original items and the retention results are presented in Appendix A.

Confirmatory Factor Analysis (CFA) was conducted to assess the measurement model for each latent construct. The results, as presented in Table 2, indicate that the measurement model fit the empirical data well across all indices. Specifically, the $\chi 2/df$ ratios for all constructs ranged from 1.21 to 3.47. These values are well below the threshold of 5.0 suggested by Hair *et al.* [57], indicating an acceptable model fit. Regarding absolute fit indices, the Root Mean Square Error of Approximation (RMSEA) values ranged from 0.02 to 0.06, satisfying the strict criterion of less than 0.08 recommended by Browne and Cudeck [58]. Furthermore, both the Goodness of Fit Index (GFI) and the Adjusted Goodness of Fit Index (AGFI) ranged from 0.95 to 1.00, exceeding the 0.90 benchmark proposed by Hu and Bentler [59]. Finally, the standardized Factor Loadings (FL) for all observed indicators ranged from 0.68 to 0.85, surpassing the critical 0.50 threshold required for convergent validity [57]. These indices collectively demonstrate that the instrument possessed sufficient measurement reliability and validity.

Table 2. First-order confirmatory factor analysis

Fit Indices	χ^2	df	χ^2/df	RMSEA	GFI	AGFI	FL
Threshold Values	---	---	< 5	< .10	> 0.80	> 0.80	> 0.50
Technological Innovation	6.028	5	1.206	0.018	0.996	0.989	0.692~0.747
AI-SE	24.136	9	2.682	0.051	0.987	0.971	0.678~0.752
AI Learning Anxiety	12.937	9	1.437	0.026	0.993	0.984	0.795~0.847
AI Literacy	93.666	27	3.469	0.062	0.968	0.946	0.693~0.761
AI Usage Satisfaction	26.759	9	2.973	0.055	0.986	0.968	0.686~0.786

B. Assessment of Common Method Variance

Given that all variables were collected via self-report questionnaires in a single survey, this study implemented both procedural and statistical remedies to control for potential Common Method Variance (CMV) [55].

In terms of procedural controls, measures were taken during the survey design phase to minimize bias. These included: (1) ensuring the strict anonymity of participants to reduce evaluation apprehension and social desirability bias; (2) providing clear instructions emphasizing that there were no right or wrong answers; and (3) using concise and simple language to avoid ambiguity in item comprehension.

In terms of statistical tests, Harman's single-factor test was employed to examine the presence of CMV [57]. An Exploratory Factor Analysis (EFA) without rotation was conducted on all measurement items. The results extracted five factors with eigenvalues greater than 1, accounting for a total cumulative variance of 62.34%. Crucially, the first unrotated factor explained only 37.136% of the variance, which is well below the critical threshold of 50% [55]. These findings indicate that common method bias was not a significant concern in this study.

C. Data Normality Assessment

Prior to structural equation modeling, the data distribution was examined to ensure the assumption of multivariate normality was met. As shown in Table 3, the skewness values ranged from −1.365 to 0.352, and the kurtosis values ranged from −1.303 to 4.756. According to the guidelines proposed by Kline [60], data is considered to be normally distributed if the absolute value of skewness is less than 3.0 and the absolute value of kurtosis is less than 10.0. All indicators in this study fell well within these recommended thresholds, indicating no severe violation of the normality assumption. Therefore, the data were deemed suitable for subsequent analysis using the Maximum Likelihood estimation method.

Table 3. Descriptive statistics and normality test

Indicators	AIM	AUEM	LAM	AIFM	EPM
Skewness	−0.330	−1.365	0.352	−0.372	−0.307
Std. Error of Skewness	0.096	0.096	0.096	0.096	0.096
Kurtosis	0.000	4.756	−1.303	1.661	0.692
Std. Error of Kurtosis	0.192	0.192	0.192	0.192	0.192

D. Reliability and Validity Analysis

For a quantitative research study to yield reliable and trustworthy results, it needs to demonstrate acceptable levels of reliability and validity. As shown in Table 4, in this study, the Cronbach's α values and Composite Reliability (CR) values for each variable ranged from 0.84 to 0.92, while Factor Loading (FL) values ranged from 0.71 to 0.82, and the

Average Variance Extracted (AVE) values ranged from 0.51 to 0.67. These results align with the standards proposed by Hair *et al*. [57], indicating acceptable numerical values. Additionally, the variables had mean scores ranging from 2.55 to 3.99, with standard deviations ranging from 0.55 to 1.05.

Construct Discriminant Validity analysis can assist researchers in identifying the absence of multicollinearity issues among variables. Initially, validity was assessed using the Fornell-Larcker criterion; as shown in Table 5, the square root of the AVE for each construct exceeded its correlation with any other construct [61], and all inter-construct correlations were below the 0.85 threshold suggested by Ahmad *et al*. [62]. To further ensure the robustness of discriminant validity, the Heterotrait-Monotrait ratio (HTMT) was examined. As recommended by Henseler *et al*. [63], HTMT values below 0.90 (and preferably below 0.85) indicate distinct constructs. As shown in Table 6, all HTMT ratios in this study were below 0.85, conclusively demonstrating adequate discriminant validity.

Table 4. Reliability and validity analysis

Construct	Items	*M*	SD	α	CR	AVE	FL
	---	---	---	> 0.70	> 0.70	> 0.50	> 0.50
Technological Innovation	5	3.742	0.728	0.840	0.841	0.514	0.716
AI-SE	6	3.817	0.652	0.862	0.861	0.507	0.712
AI Learning Anxiety	6	2.554	1.048	0.923	0.923	0.667	0.817
AI Literacy	9	3.988	0.548	0.906	0.905	0.515	0.717
AI Usage Satisfaction	6	3.854	0.663	0.881	0.884	0.561	0.744

Table 5. Construct discriminant validity

Construct	1	2	3	4	5
1. Technological Innovation	(0.717)				
2. AI-SE	0.559	(0.712)			
3. AI Learning Anxiety	−0.441	−0.424	(0.818)		
4. AI Literacy	0.542	0.0554	−0.443	(0.718)	
5. AI Usage Satisfaction	0.536	0.587	−0.357	0.512	(0.749)

Table 6. HTMT analysis results

Construct	1	2	3	4	5
1. Technological Innovation	1				
2. AI-SE	0.656	1			
3. AI Learning Anxiety	0.621	0.627	1		
4. AI Literacy	0.626	0.674	0.579	1	
5. AI Usage Satisfaction	0.499	0.474	0.482	0.398	1

E. Overall Structural Model Fit Results

To ensure the adequacy of the research model, after conducting measurement model analysis and reliability and validity assessments, an overall structural model fit evaluation was necessary for model validation. During this stage, eight indicators, RMSEA, GFI, AGFI, Normed Fit Index (NFI), Non-Normed Fit Index (NNFI), Comparative Fit Index (CFI), Incremental Fit Index (IFI), and Relative Fit Index (RFI), should all be higher than 0.80. Additionally, two indicators, Parsimonious Normed Fit Index (PNFI) and Parsimonious Goodness of FIT index (PGFI), should be higher than 0.50. The fit indices for this study were as follows: $\chi^2 = 863.28$, $df = 48$, $\chi^2/df = 1.88$, RMSEA = 0.04, GFI =0 .92, AGFI = 0.91, NFI = 0.93, NNFI = 0.96, CFI = 0 .96, IFI = 0 .96, RFI = 0.92, PNFI = 0.85, PGFI = 0.80, and Standardized RMR (SRMR) = 0.07. These results all align with the acceptable numerical standards proposed by Abedi *et al*. [64] and Hair *et al*. [57].

F. Structural Model Validation Results

Using the AMOS software to validate the results revealed the following relationships: Technological innovation was positively correlated with AI self-efficacy (β = 0.68***); Technological innovation was negatively correlated with AI learning anxiety (β = −0.33***); AI self-efficacy was negatively dependent on AI learning anxiety (β = −0.25***); AI self-efficacy and AI literacy showed a positive correlation (β = 0.56***); AI learning anxiety and AI literacy were negatively correlated (β = −0.23***); and AI literacy and AI usage satisfaction were positively correlated (β = 0.61***). These validation results supported all six research hypotheses, as illustrated in Fig. 2.

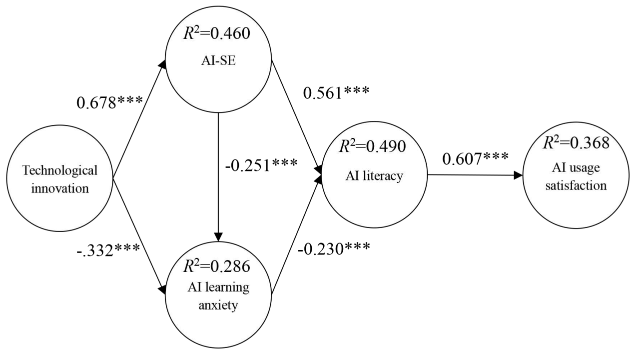

Fig. 2. Structural equation modeling results (***p < 0.001).

V. Discussion

A. Technological Innovation Is Positively Correlated with AI Self-Efficacy but Negatively Correlated with AI Learning Anxiety

This study posited that technological innovation may influence individuals' cognitive and emotional responses to AI, aligning with the core tenets of Parasuraman's Technology Readiness Index theory [19]. Findings revealed that technological innovation positively correlates with AI self-efficacy while negatively correlating with AI learning anxiety, confirming both Hypotheses H1 and H2. Specifically, vocational students with higher technological readiness typically exhibit greater optimism and innovativeness, demonstrating greater willingness to explore and master new technologies, thereby enhancing their self-efficacy during AI learning [38]. Simultaneously, when encountering AI learning obstacles, vocational students are better equipped to alleviate anxiety stemming from uncertainty through effective cognitive and behavioral strategies. Furthermore, the positive relationship between technological innovation and self-efficacy can be explained by factors such as "sense of mastery in problem-solving" and "adaptive learning strategies." The negative impact of technological innovation on learning anxiety manifests in aspects such as "higher tolerance for uncertainty" and "more positive attribution of failure."

B. AI Self-Efficacy Is Negatively Correlated with AI Learning Anxiety but Positively Correlated with AI Literacy

Despite AI's rapid penetration into educational settings, it elicits polarized emotional responses. On one hand, students experience learning substitution anxiety due to perceptions that "AI performs tasks faster and better than I do." On the other hand, students who believe they "can master AI" perceive generative AI tools as extensions of their capabilities, proactively exploring more advanced applications [65]. This study found a significant negative correlation between "AI self-efficacy" and "AI learning anxiety," validating Hypothesis H3 and aligning with Asio and Sardina [66]. They argue that users with higher AI self-efficacy typically possess greater confidence in their ability to operate and comprehend AI systems. This belief effectively mitigates uncertainty and frustration during technology use, thereby significantly reducing anxiety levels.

Furthermore, this study found a positive correlation between AI self-efficacy and AI literacy, validating Hypothesis H4. This aligns with the findings of He *et al*. [67] and reinforces the PPT framework, which emphasizes the central role of the "people" factor in technology adoption. An individual's familiarity with technology influences their self-efficacy [68]. Specifically, vocational college students with higher AI literacy typically possess a deeper understanding of AI technology. As students repeatedly engage with and utilize AI-related tools during their learning journey, their self-efficacy increases with practice frequency. This boosts their willingness to tackle challenging tasks, creating a virtuous cycle that progressively builds more comprehensive and systematic AI literacy. This finding empirically supports the TRI, which posits that individuals' intrinsic beliefs are key determinants of their technology mastery outcomes.

C. AI Literacy Correlates Negatively with AI Learning Anxiety but Positively with AI User Satisfaction

This study confirms that AI literacy is negatively correlated with AI learning anxiety (H5) but positively influences user satisfaction (H6). Regarding H5, the findings indicate that competencies acquired through learning reduce anxiety, consistent with research suggesting that limited knowledge fuels fear [69] whereas literacy mitigates perceived risks [70, 71]. From a TRI perspective, enhanced knowledge and innovation capabilities lower psychological discomfort and perceived risk, enabling effective AI application [19]. Regarding H6, the positive impact on satisfaction aligns with prior evidence that technology acceptance and skill development drive usage outcomes [72]. Specifically, anxiety hinders competence through "cognitive avoidance," while literacy enhances satisfaction via "task-solving capabilities" and an "increased sense of control" [73]. These dynamics resonate with the PPT framework [35], illustrating how internal states (anxiety) shape the interaction process (learning), ultimately determining the quality of technology application.

D. Implications

This study makes several contributions to the field. First, it focused on the specific group of vocational college students, conducting empirical exploration under the backdrop of national AI education strategies and industry-education integration policies. Through empirical surveys of vocational college students, the study validated the operational mechanisms linking technological innovation, AI self-efficacy, learning anxiety, AI literacy, and usage satisfaction. This not only expands the applicability and explanatory power of the TRI and PPT framework within AI education contexts, but also provides localized empirical support for understanding the psychological mechanisms and behavioral patterns of vocational college students during technological learning. This aligns with China's policy direction of promoting deep integration between AI and vocational education.

Second, this study offers significant practical implications for AI education in vocational institutions. Empirical findings indicate that enhancing students' AI self-efficacy and AI literacy effectively alleviates AI learning anxiety while increasing their acceptance of AI technology and satisfaction with its use. Given the learning characteristics and career-oriented focus of vocational students, institutions should prioritize cultivating a developmental mindset of "continuously iterating digital literacy," encouraging proactive engagement with technological change rather than resistance to tech-enabled learning. Practical teaching efforts should emphasize four main points: first, embedding real-world enterprise cases and industry AI applications into curricula, such as smart device fault diagnosis and educational large-language-model-assisted instructional design; second, designing tiered practical training tasks, progressing from basic AI tool usage to complex human-machine collaborative projects, helping students build confidence through successful experiences; third, strengthening ethical scenario discussions and critical usage awareness, such as incorporating privacy protection and industry ethical standards into AI tool usage discussions to prevent a disconnect between technology application and professional practice; and finally, emphasizing the integration of "AI + professional expertise" rather than mere technical operation, truly making AI a supportive tool that empowers vocational students' career growth.

Finally, regarding methodological recommendations, it is imperative to strengthen academic ethics education. Institutions must guide students to critically evaluate AI-generated content to prevent "cognitive outsourcing" and technological dependency. Acknowledging that technology is a "double-edged sword," educators must address potential usage barriers or psychological burdens arising from system mismatches. Establishing clear guidelines for responsible AI use will help mitigate these risks, ensuring that digital transformation enhances rather than hinders educational quality.

In summary, this study offers recommendations for technology integration and talent cultivation in vocational institutions during the AI era, addressing theoretical frameworks, educational practices, and ethical standards.

E. Research Limitations and Future Study

This study has several limitations that warrant further investigation. First, it primarily focuses on variables related to psychological cognition and satisfaction levels, excluding behavioral variables such as actual usage and performance outcomes. While satisfaction serves as a key antecedent for predicting behavioral intentions, future research should integrate specific behavioral models to more comprehensively reveal the actual impact of AI literacy on educational outcomes. It is recommended that future studies incorporate dynamic learning analytics models to examine students' AI-empowered learning performance. Second, the sample exclusively comprised students from Chinese vocational colleges. While this group exhibits distinct representativeness, its homogeneity in terms of age, educational background, and cultural context may limit the generalizability of the findings to other populations. Subsequent studies should validate the model's robustness using samples from general universities and corporate employees. Furthermore, this research did not sufficiently examine the moderating effects of demographic variables (e.g., gender, age, major background) and organizational context variables. For instance, students from different majors may exhibit varying levels of adaptability to AI technology, and differing anxiety thresholds. Future studies could employ multi-group analyses to more precisely identify associations between group differences and technology usage outcomes.

Finally, as generative AI undergoes rapid iteration, its social acceptance and functional maturity remain in flux. According to Gartner's Hype Cycle, current AIGC technology is transitioning from the "Peak of Inflated Expectations" toward the "Trough of Disillusionment." Against this backdrop, individual psychological and behavioral mechanisms may undergo significant shifts alongside technological evolution. Therefore, future research could adopt longitudinal studies to compare the evolution paths of individual cognition, AI anxiety, and AI satisfaction across different stages of technological maturity. This approach would sustainably reveal the dynamic relationship between technology and humans. As an emerging technology, AI still lacks robust evidence to explain many educational phenomena and impacts, and the underlying emerging variables and theories within this phenomenon require further exploration.

VI. Conclusions

This study, grounded in the TRI and PPT frameworks, examined the relationships among technological innovation, AI self-efficacy, AI learning anxiety, AI literacy, and usage satisfaction. The three major findings are as follows: (1) Technological innovation positively correlates with AI self-efficacy but negatively correlates with AI learning anxiety; (2) AI self-efficacy negatively correlates with AI learning anxiety but positively correlates with AI literacy; and (3) AI literacy negatively correlates with AI learning anxiety but positively correlates with AI usage satisfaction. These findings suggest that enhancing individuals' technological innovation and AI self-efficacy not only alleviates anxiety during technology use but also fosters AI literacy, ultimately leading to higher application satisfaction. At the educational and practical levels, emphasis should be placed on building cognitive competence and mastery through successful experiences and contextualized task design, enabling individuals to achieve a truly empowering rather than dependent mode of technology use. Simultaneously, vigilance is needed against short-sighted behaviors that prioritize satisfaction at the expense of competency development, advocating for responsible AI usage ethics.

Theoretically, this study elucidates the transformation mechanism where "psychological readiness" drives "capability accumulation," offering a nuanced perspective on bridging the digital divide caused by affective barriers. Ultimately, fostering this symbiotic human-AI relationship, grounded in psychological adaptability rather than mere tool proficiency, is essential for shaping a resilient vocational workforce capable of navigating the complexities of the intelligent era.

Appendix

Table A1. Measurement items and retention results

	Items	Results
Technological Innovation	1. In my social circle, I'm usually the first to try new tech products.	Keep
	2. If I learn about the latest tech products, I'll be interested in using them.	Keep
	3. Compared to my friends, I always use the newest tech products.	Keep
	4. Even if I've never heard of this latest tech product before, I'd still want to try it.	Keep
	5. In my social circle, I'm usually the first to recognize the latest tech brands.	Delete
	6. My knowledge of the latest tech products surpasses that of others.	Keep
AI-SE	1. I know how to apply AI technology effectively.	Keep
	2. When AI outputs are unsatisfactory, I know how to quickly adjust the instructions.	Keep
	3. I am confident in handling unexpected issues with AI applications.	Keep
	4. With effort, I can resolve any problems arising from AI applications.	Keep
	5. If new AI application issues emerge, I can solve them independently.	Keep
	6. When facing AI application challenges, I can overcome them by dedicating more time.	Keep
AI Learning Anxiety	1. I worry that I won't be able to master AI applications.	Keep
	2. I lack confidence in learning AI applications.	Keep
	3. I'm concerned that AI technology updates too rapidly, making it difficult to learn.	Keep
	4. Understanding the logic behind AI usage requires a certain aptitude, which is challenging for me.	Keep
	5. I'm concerned that AI has too many auxiliary features, making it hard for me to learn.	Keep
	6. I worry that AI commands are overly complex, making it difficult for me to learn.	Keep
AI Literacy	1. I know how to use some basic AI tools or applications.	Keep
	2. I am familiar with common AI applications in daily life.	Keep
	3. I understand how AI operates.	Delete
	4. I have experience interacting with AI applications in real life.	Keep
	5. I understand the use cases for AI applications.	Keep
	6. I am aware of the advantages and disadvantages of AI applications.	Keep
	7. I am aware of the potential ethical challenges posed by AI.	Keep

	8. I am aware of AI's potential societal impacts.	Delete
	9. I understand AI development trends.	Keep
	10. I comprehend AI's influence on the future labor market.	Delete
	11. I can effectively use AI tools to solve everyday problems.	Keep
	12. I am willing to try new AI technologies or applications.	Keep
AI Usage Satisfaction	1. I find AI's feedback to be very timely.	Keep
	2. I find AI's responses to questions to be very fluent.	Keep
	3. I find the information presented by AI to be very clear.	Keep
	4. I find AI's answers to be very reliable.	Delete
	5. I find AI's answers to be very accurate.	Keep
	6. I find AI's responses to be logically coherent.	Keep
	7. I find AI's solutions to be very dependable.	Delete
	8. I find AI's solutions to be very effective.	Keep

CONFLICT OF INTEREST

The authors declare no conflict of interest.

AUTHOR CONTRIBUTIONS

Li Liao conceptualized the study; processed the data; and wrote the original draft of the manuscript; Jian-Hong Ye contributed to the methodology, supervised the data analysis, provided critical revisions to the conceptual framework, and served as the corresponding author; all authors have read and agreed to the published version of the manuscript.

FUNDING

This work was financially supported by the National Social Science Fund of China under the Major Project, "Research on the Interactive Evolution Law of Vocational Education and Socioeconomic Systems" (Grant No.: 24&ZD178).

REFERENCES

[1] J. H. Ye, X. Yang, M. Zhang, W. Nong, and L. Wang, "The relationship between inert thinking and ChatGPT dependence: An I-PACE model perspective," *Educ. Inf. Technol.*, vol. 30, pp. 3885–3909, Feb. 2025.

[2] J. H. Ye, Z. He, B. Bai, and Y. F. Wu, "Sustainability of Technical and Vocational Education and Training (TVET) along with vocational psychology," *Behav. Sci.*, vol. 14, no. 10, 859, Sep. 2024.

[3] M. Zhang, J. H. Ye, and X. Yang, "Watch out for errors! Factors related to ChatGPT skepticism: A cognitive perspective," *Interact. Learn. Environ.*, vol. 33, no. 6, pp. 3985–3999, Jan. 2025.

[4] M. Abubakre, Y. Zhou, and Z. Zhou, "The impact of information technology culture and personal innovativeness in information technology on digital entrepreneurship success," *Inf. Technol. People*, vol. 35, no. 1, pp. 204–231, Jan. 2022.

[5] W. Tang, W. Chaiyasoonthorn, and S. Chaveesuk, "Understanding the impact of self-efficacy, personal innovativeness and content quality on mobile learning usage in higher vocational colleges," *Espacio Tiempo y Educacion,* vol. 11, no. 1, Jan.–June 2024.

[6] H. Yang and S. S. Sundar, "AI anxiety: Explication and exploration of effect on state anxiety when interacting with AI doctors," *Comput. Hum. Behav. Artif. Humans*, vol. 3, 100128, Mar. 2025.

[7] K. A. Cho and Y. H. Seo, "Dual mediating effects of anxiety to use and acceptance attitude of artificial intelligence technology on the relationship between nursing students' perception of and intention to use them: a descriptive study," *BMC Nurs*., vol. 23, no. 1, 212, Mar. 2024.

[8] Y. Ji, M. Zhong, S. Lyu, T. Li, S. Niu, and Z. Zhan, "How does AI literacy affect individual innovative behavior: the mediating role of psychological need satisfaction, creative self-efficacy, and self-regulated learning," *Educ. Inf. Technol*., vol. 30, pp. 16133–16162, Feb. 2025.

[9] F. Wang, R. B. King, C. S. Chai, and Y. Zhou, "University students' intentions to learn artificial intelligence: The roles of supportive environments and expectancy–value beliefs," *Int. J. Educ. Technol. High. Educ*., vol. 20, no. 1, 51, Aug. 2023.

[10] D. T. K. Ng, W. Luo, H. M. Y. Chan, and S. K. W. Chu, "Using digital story writing as a pedagogy to develop AI literacy among primary students," *Comput. Educ. Artif. Intell*., vol. 3, 100054, Feb. 2022.

[11] C. S. Chai, P. Y. Lin, M. S. Y. Jong, Y. Dai, T. K. Chiu, and J. Qin, "Perceptions of and behavioral intentions towards learning artificial intelligence in primary school students," *Educ. Technol. Soc*., vol. 24, no. 3, pp. 89–101, July 2021.

[12] H. Choung, P. David, and A. Ross, "Trust in AI and its role in the acceptance of AI technologies," *Int. J. Hum.–Comput. Interact*., vol. 39, no. 9, pp. 1727–1739, Apr. 2023.

[13] Y. Sun, J. C. Hong, J. H. Ye, and J. N. Ye, "Satisfaction with online study abroad predicted by motivation and self-efficacy: A perspective based on the situated expectancy–value theory during the COVID-19 epidemic," *Sustainability*, vol. 15, no. 5, 4070, Feb. 2023.

[14] J. H. Ye, M. Y. Chen, and Y. W. Hao, "Editorial: Exploring the psychology of vocational education: From the perspective of literacy promotion," *Front. Psychol*., vol. 14, 1167176, Mar. 2023.

[15] C. Chen, W. Hu, and X. Wei, "From anxiety to action: Exploring the impact of artificial intelligence anxiety and artificial intelligence self-efficacy on motivated learning of undergraduate students," *Interact. Learn. Environ*., vol. 33, no. 4, pp. 3162–3177, Dec. 2024.

[16] A. Bewersdorff, M. Hornberger, C. Nerdel, and D. S. Schiff, "AI advocates and cautious critics: How AI attitudes, AI interest, use of AI, and AI literacy build university students' AI self-efficacy," *Comput. Educ. Artif. Intell.*, vol. 8, 100340, June 2025.

[17] M. Abuadas and Z. Albikawi, "Predicting nursing students' behavioral intentions to use AI: The interplay of ethical awareness, digital literacy, moral sensitivity, attitude, self-efficacy, anxiety, and social influence," *J. Hum. Behav. Soc. Environ.*, pp. 1–21, Mar. 2025.

[18] A. Parasuraman, "Technology Readiness Index (TRI) a multiple-item scale to measure readiness to embrace new technologies," *J. Serv. Res*., vol. 2, no. 4, pp. 307–320, May 2000.

[19] A. Parasuraman and C. L. Colby, "An updated and streamlined Technology Readiness Index: TRI 2.0," *J. Serv. Res*., vol. 18, no. 1, pp. 59–74, June 2014.

[20] C. Wu and G. G. Lim, "Investigating older adults users' willingness to adopt wearable devices by integrating the technology acceptance model (UTAUT2) and the technology readiness index theory," *Front. Public Health*, vol. 12, 1449594, Sep. 2024.

[21] A. Satwekar, M. Miozza, C. Abbattista, S. Palumbo, and M. Rossi, "Triad of digital transformation: Holistic orchestration for people, process, and technology," *IEEE Trans. Eng. Manag*., vol. 71, pp. 7815–7831, Apr. 2024.

[22] J. Adamek and M. Solarz, "Determinants of artificial intelligence use by accounting practitioners from the perspective of the Technology Readiness and Acceptance Model (TRAM)," *Zesz. Teor. Rachun*., vol. 49, no. 2, June 2025.

[23] B. Zhou, L. Q. Zhou, and M. Y. Wu, "Influence of augmented reality on tourists' tourism intention in the context of smart tourism: A revised model based on technology acceptance model," *J. Bus. Econ*., vol. 2, pp. 71–79, Apr. 2017.

[24] S. C. Chen, S. H. Li, S. C. Liu, D. C. Yen, and A. Ruangkanjanases, "Assessing determinants of continuance intention towards personal cloud services: Extending utaut2 with technology readiness," *Symmetry*, vol. 13, no. 3, 467, Mar. 2021.

[25] Y. Zhao, Y. Li, X. Xiao, H. Chang, and B. Liu, "Factors influencing the acceptance of ChatGPT in high education: An integrated model with PLS-SEM and fsQCA approach," *Sage Open*, vol. 14, no. 4, Oct. 2024.

[26] M. Astuti, Z. Arifin, F. Mutohhari, and M. Nurtanto, "Competency of digital technology: the maturity levels of teachers and students in vocational education in Indonesia," *J. Educ. Technol*., vol. 5, no. 2, pp. 254–262, July 2021.

[27] S. I. Shakeel, M. F. A. Haolader, and M. S. Sultana, "Exploring dimensions of blended learning readiness: Validation of scale and assessing blended learning readiness in the context of TVET Bangladesh," *Heliyon*, vol. 9, no. 1, Jan. 2023.

[28] M. Moca and A. Badulescu, "Determinants of economical high school students' attitudes toward mobile devices use," *Sustainability*, vol. 15,

no. 12, 9331, June 2023.
[29] H. J. Leavitt, "Applied organizational change in industry: structural, technical and human approaches," in *New Perspectives in Organization Research*, W. W. Cooper, H. J. Leavitt, and M. W. I. Shelly, Eds. New York, NY, USA: Wiley, 1964, pp. 55–71.
[30] J. S. Edwards, "Artificial intelligence and knowledge management: How much difference can it really make?" in *Proc. KMAC2000*, J. S. Edwards and J. B. Kidd, Eds. Birmingham, UK: Operational Research Society, 2000, pp. 136–147.
[31] P. Gongla and C. R. Rizzuto, "Evolving communities of practice: IBM global," *IBM Syst. J.*, vol. 40, pp. 842–862, Sep. 2001.
[32] B. Schneier, *Schneier on Security*, New York, NY, USA: Wiley, 1999.
[33] M. Parent and B. Cusack, "Cybersecurity in 2016: People, technology, and processes," *Bus. Horizons*, vol. 59, no. 6, pp. 567–569, Nov. 2016.
[34] M. Tarafdar, C. M. Beath, and J. W. Ross, "Using AI to enhance business operations," *MIT Sloan Manage. Rev*., vol. 60, no. 4, pp. 37–44, July 2019.
[35] E. E. Makarius, D. Mukherjee, J. D. Fox, and A. K. Fox, "Rising with the machines: A sociotechnical framework for bringing artificial intelligence into the organization," *J. Bus. Res*., vol. 120, pp. 262–273, Oct. 2020.
[36] L. Saari, O. Kuusisto, and S. Pirttikangas, "AI maturity web tool helps organisations proceed with AI," VTT Technical Research Centre of Finland, VTT White Paper, 2019.
[37] M. Blut and C. Wang, "Technology readiness: a meta-analysis of conceptualizations of the construct and its impact on technology usage," *J. Acad. Mark. Sci*., vol. 48, no. 4, pp. 649–669, July 2020.
[38] A. Bandura, "Social cognitive theory for personal and social change by enabling media," in *Entertainment-Education and Social Change*, A. Singhal, M. J. Cody, E. M. Rogers, and M. Sabido, Eds. Mahwah, NJ, USA: Lawrence Erlbaum Associates, 2003, pp. 97–118.
[39] K. Nuutila, A. Tapola, H. Tuominen, S. Kupiainen, A. Pásztor, and M. Niemivirta, "Reciprocal predictions between interest, self-efficacy, and performance during a task," *Front. Educ.*, vol. 5, pp. 36–42, June 2020.
[40] K. A. Renninger, "Working with and cultivating interest, self-efficacy, and self-regulation," in *Innovations in Educational Psychology: Perspectives on Learning, Teaching and Human Development*, D. D. Preiss and R. J. Sternberg, Eds. New York, NY, USA: Springer, 2010, pp. 158–195.
[41] G. Xu, "The Impact of Artificial Intelligence Anxiety on Employee Deviant Behavior: A Moderated Mediation Model," *East China Econ. Manage*., vol. 37, no. 11, pp. 120–128, Nov. 2023
[42] J. M. R. Asio and A. N. Suero, "Artificial intelligence anxiety, self-efficacy, and self-competence among students: Implications to higher education institutions," *Educ. Policy Dev*., vol. 2, no. 2, pp. 82–93, Apr. 2024.
[43] S. Bećirović, E. Polz, and I. Tinkel, "Exploring students' AI literacy and its effects on their AI output quality, self-efficacy, and academic performance," *Smart Learn. Environ*., vol. 12, no. 1, 29, Jan. 2025.
[44] M. A. Almaiah, M. M. Alamri, and W. Al-Rahmi, "Applying the UTAUT model to explain the students' acceptance of mobile learning system in higher education," *IEEE Access*, vol. 7, pp. 174673–174686, Dec. 2019.
[45] Y. Liu, Y. Li, K. Song, and F. Chu, "The two faces of Artificial Intelligence (AI): Analyzing how AI usage shapes employee behaviors in the hospitality industry," *Int. J. Hosp. Manag.*, vol. 122, 103875, Oct. 2024.
[46] L. Wang and W. Li, "The Impact of AI Usage on University Students' Willingness for Autonomous Learning," *Behav. Sci.*, vol. 14, no. 10, 956, Oct. 2024.
[47] L. J. Labrague, R. Aguilar-Rosales, B. C. Yboa, and J. B. Sabio, "Factors influencing student nurses' readiness to adopt Artificial Intelligence (AI) in their studies and their perceived barriers to accessing AI technology: A cross-sectional study," *Nurse Educ. Today*, vol. 130, 105945, Oct. 2023.
[48] J. C. Hong, P. H. Lin, and P. C. Hsieh, "The effect of consumer innovativeness on perceived value and continuance intention to use smartwatch," *Comput. Hum. Behav*., vol. 67, pp. 264–272, Mar. 2017.
[49] M. Y. Lin, J. C. Hong, K. H. Tai, and P. H. Jiang, "ChatGPT addiction predicted by openness to using new technology and self-efficacy, and reflected in continuous intention," *Interact. Learn. Environ*., pp. 1–15, Jan. 2025.
[50] J. Li and J. S. Huang, "Dimensions of artificial intelligence anxiety based on the integrated fear acquisition theory," *Technol. Soc*., vol. 63, 101410, Nov. 2020.
[51] J. F. Hair Jr, G. T. M. Hult, C. M. Ringle, M. Sarstedt, N. P. Danks, and S. Ray, *Partial Least Squares Structural Equation Modeling (PLS-SEM) Using R: A Workbook*, Springer Nature, 2021.
[52] L. J. Jobst, M. Bader, and M. Moshagen, "A tutorial on assessing statistical power and determining sample size for structural equation models," *Psychol. Methods*, vol. 28, no. 1, pp. 207–221, Jan. 2023.
[53] M. J. Zyphur, C. V. Bonner, and L. Tay, "Structural equation modeling in organizational research: The state of our science and some proposals for its future," *Annu. Rev. Organ. Psychol. Organ. Behav*., vol. 10, pp. 495–517, Jan. 2023.
[54] J. C. Anderson and D. W. Gerbing, "Structural equation modeling in practice: A review and recommended two-step approach," *Psychol. Bull*, vol. 103, no. 3, pp. 411–423, Mar. 1988.
[55] P. M. Podsakoff, S. B. MacKenzie, J. Y. Lee, and N. P. Podsakoff, "Common method biases in behavioral research: A critical review of the literature and recommended remedies," *J. Appl. Psychol.*, vol. 88, no. 5, pp. 879–903, Sep. 2003.
[56] F. Kock, A. Berbekova, and A. G. Assaf, "Understanding and managing the threat of common method bias: Detection, prevention and control," *Tourism Manag*., vol. 86, 104330, Oct. 2021.
[57] J. F. Hair, W. C. Black, B. J. Babin, R. E. Anderson, and R. L. Tatham, *Multivariate Data Analysis*, 8th ed. Cengage, 2019.
[58] M. W. Browne and R. Cudeck, "Alternative ways of assessing model fit," in *Testing Structural Equation Models*, K. A. Bollen and J. S. Long, Eds. Newbury Park, CA, USA: Sage, 1993, pp. 136–162.
[59] L. T. Hu and P. M. Bentler, "Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives," *Struct. Equ. Modeling*, vol. 6, no. 1, pp. 1–55, Jan. 1999.
[60] R. B. Kline, *Principles and Practice of Structural Equation Modeling*, 4th ed. Guilford Publications, 2015.
[61] G. W. Cheung, H. D. Cooper-Thomas, R. S. Lau, and L. C. Wang, "Reporting reliability, convergent and discriminant validity with structural equation modeling: A review and best-practice recommendations," *Asia Pac. J. Manag*., vol. 41, pp. 745–783, June 2024.
[62] S. Ahmad, N. N. A. Zulkurnain, and F. I. Khairushalimi, "Assessing the validity and reliability of a measurement model in structural equation modeling (SEM)," *J. Adv. Math. Comput. Sci*., vol. 15, no. 3, pp. 1–8, May 2016.
[63] J. Henseler, C. M. Ringle, and M. Sarstedt, "A new criterion for assessing discriminant validity in variance-based structural equation modeling," *J. Acad. Mark. Sci*., vol. 43, no. 1, pp. 115–135, Jan. 2015.
[64] G. Abedi, F. Rostami, and A. Nadi, "Analyzing the dimensions of the quality of life in hepatitis B patientsusing confirmatory factor analysis," *Global J. Health Sci*., vol. 7, no. 7, pp. 22–31, Nov. 2015.
[65] Y. Hwang and Y. Wu, "The influence of generative artificial intelligence on creative cognition of design students: a chain mediation model of self-efficacy and anxiety," *Front. Psychol*., vol. 15, 1455015, Sep. 2024.
[66] J. M. R. Asio and D. P. Sardina, "Gender differences on the impact of AI self-efficacy on AI anxiety through AI self-competency: A moderated mediation analysis," *J. Pedagogical Res*., vol. 9, no. 2, pp. 55–71, Apr. 2025.
[67] T. He, J. Huang, Y. Li, L. Wang, J. Liu, F. Zhang *et al*., "The mediation effect of AI self-efficacy between AI literacy and learning engagement in college nursing students: A cross-sectional study," *Nurse Educ. Practice*, vol. 81, 104499, Jan. 2025.
[68] O. S. Falebita and P. J. Kok, "Artificial intelligence tools usage: A structural equation modeling of undergraduates' technological readiness, self-efficacy and attitudes," *J. STEM Educ. Res*., vol. 8, no. 2, pp. 257–282, June 2025.
[69] S. Hopcan, G. Türkmen, and E. Polat, "Exploring the artificial intelligence anxiety and machine learning attitudes of teacher candidates," *Educ. Inf. Technol*., vol. 29, pp. 7281–7301, June 2024.
[70] E. Alasadi and R. Baiz, "Generative AI in education and research: Opportunities, concerns, and solutions," *J. Chem. Educ*., vol. 100, no. 8, pp. 2965–2971, Aug. 2023.
[71] G. Bilquise, S. Ibrahim, and S. E. M. Salhieh, "Investigating student acceptance of an academic advising chatbot in higher education institutions," *Educ. Inf. Technol*., pp. 1–26, June 2023.
[72] S. Yun, G. Park, and L. Lee, "Dynamics of ChatGPT literacy: Impact of trust, usefulness, self-efficacy, and user satisfaction," *Curr. Psychol*., vol. 44, pp. 13746–13755, Jan. 2025.
[73] J. H. Ye, Y. W. Hao, and Y. F. Wu, "Effectiveness and sustainable applications of educational technology," *Sustainability*, vol. 16, no. 18, 8209, Sep. 2024.