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EXPLAINING HIGHER VOCATIONAL COMPUTER-MAJOR STUDENTS' ATTITUDES TOWARD AN AI TEACHING PLATFORM: THE ROLES OF TASK–TECHNOLOGY FIT AND PERCEIVED USEFULNESS

ANÁLISE DAS ATITUDES DE ALUNOS DO CURSO TÉCNICO SUPERIOR DE INFORMÁTICA EM RELAÇÃO A UMA PLATAFORMA DE ENSINO DE IA: O PAPEL DA ADEQUAÇÃO ENTRE TAREFA E TECNOLOGIA E DA UTILIDADE PERCEBIDA

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Weihao Ouyang*
***Dhurakij Pundit University, Bangkok, Thailand
djtiger@live.com

Yuan-Cheng Chang*
***Dhurakij Pundit University, Bangkok, Thailand
yuan-cheg.cha@dpu.ac.th

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Abstract
As artificial intelligence continues to permeate vocational education, promoting students' effective use of AI teaching platforms has become an important issue in instructional reform. Grounded in the Technology acceptance model (TAM), this study introduces task-technology fit (TTF) as an additional explanatory variable and examines the structural relationships among TTF, perceived usefulness (PU), and attitude toward using (ATU) AI teaching platforms among students in computer-related majors at higher vocational colleges. Using a stratified two-stage sampling method, a questionnaire survey was administered to 716 students from higher vocational colleges in Hunan Province. Structural Equation Modeling (SEM) was employed for empirical testing, and the results indicate a good model fit. The findings show that TTF has a significant positive effect on PU, suggesting that the alignment between platform functions and professional learning tasks provides an important basis for students' usefulness perceptions. PU significantly and positively influences ATU, highlighting the critical role of perceived pragmatic value in platform acceptance. In addition, TTF also has a significant positive effect on ATU, indicating that it not only enhances students' PU but also directly fosters positive attitudes toward platform use. Based on these findings, it is recommended that vocational colleges and platform developers optimize platform functions and learning workflows around the practical training tasks and learning scenarios of computer majors.

Resumo
À medida que a inteligência artificial continua a se integrar ao ensino profissionalizante, promover o uso eficaz das plataformas de ensino baseadas em IA pelos alunos tornou-se uma questão importante na reforma pedagógica. Com base no Modelo de Aceitação da Tecnologia (TAM), este estudo introduz a adequação tarefa-tecnologia (TTF) como uma variável explicativa adicional e examina as relações estruturais entre a TTF, a utilidade percebida (PU) e a atitude em relação ao uso (ATU) de plataformas de ensino de IA entre alunos de cursos relacionados à informática em faculdades de ensino profissionalizante superior. Utilizando um método de amostragem estratificada em duas etapas, foi aplicado um questionário a 716 alunos de faculdades profissionais de nível superior na província de Hunan. A Modelagem de Equações Estruturais (SEM) foi empregada para testes empíricos, e os resultados indicam um bom ajuste do modelo. Os resultados mostram que o TTF tem um efeito positivo significativo sobre a PU, sugerindo que o alinhamento entre as funções da plataforma e as tarefas de aprendizagem profissional fornece uma base importante para as percepções de utilidade dos alunos. A PU influencia de forma significativa e positiva a ATU, destacando o papel crítico do valor pragmático percebido na aceitação da plataforma. Além disso, o TTF também tem um efeito positivo significativo sobre a ATU, indicando que ele não apenas aumenta a PU dos alunos, mas também promove diretamente atitudes positivas em relação ao uso

Strengthening platform support for discipline-specific tasks can enhance students' perceived usefulness and positive attitudes, thereby facilitating the effective application of AI in higher vocational computer education.

Keywords: Technology Acceptance Model. Structural Equation Modeling. Computer-related Majors. Educational Technology. Technology Adoption.

da plataforma. Com base nessas descobertas, recomenda-se que as faculdades de ensino profissionalizante e os desenvolvedores de plataformas otimizem as funções da plataforma e os fluxos de trabalho de aprendizagem em torno das tarefas de treinamento prático e dos cenários de aprendizagem dos cursos de informática. Fortalecer o suporte da plataforma para tarefas específicas da disciplina pode aumentar a utilidade percebida e as atitudes positivas dos alunos, facilitando assim a aplicação eficaz da IA no ensino superior profissionalizante de informática.

Palavras-chave: *Modelo de Aceitação de Tecnologia. Modelagem de Equações Estruturais. Cursos relacionados à informática. Tecnologia Educacional. Adoção de Tecnologia.*

1 INTRODUCTION

Currently, the world is entering the Fourth Industrial Revolution, centered on information technology. Artificial Intelligence (AI) is developing rapidly, profoundly reshaping the landscape of various industries and transforming the field of education at an unprecedented speed (Abulibdeh *et al*., 2024; Kayyali, 2024). From intelligent tutoring systems and adaptive learning platforms to virtual reality environments, AI is permeating every aspect of education (Adel, 2024). These technologies are driving changes in teaching models, content, and methods, while fostering positive attitudes among teachers and students toward educational technology integration (Ahmad *et al*., 2024; Al-Hattali *et al*., 2024). AI-driven applications—such as adaptive learning platforms, intelligent tutoring, and assessment systems—are generally associated with improved learning performance and teaching efficiency, particularly regarding personalized support and the optimization of learning resources and feedback mechanisms (Wang *et al*., 2024). Furthermore, AI can enhance the accessibility and operational efficiency of education systems by reducing learning barriers, automating management and assessment processes, and supporting data-driven decision-making and curriculum improvement. Consequently, these advancements contribute to the realization of global education goals

(Fitas, 2025). Overall, the application of AI in education continues to expand (Chen *et al*., 2020).

In this wave of transformation, higher vocational colleges have become increasingly prominent as vital bases for cultivating high-caliber technical and skilled personnel (Han *et al*., 2023; Chen & Pastore, 2024). Unlike research-oriented universities, talent development in higher vocational colleges emphasizes the integration of industry and education, as well as work-integrated learning (WIL). Guided by professional competency standards, this model highlights job-specific skills and practical operations (Hui, 2017; Pan *et al*., 2016). Specifically, learning tasks for students in computer-related majors are often project-based and situated in authentic contexts, requiring students to adapt quickly to rapid technological iterations (Huang, 2024; Wu *et al*., 2024). However, AI-integrated teaching platforms usually feature complex functions and higher technical barriers, which may hinder students' acceptance of these platforms (Bernabei *et al*., 2023). If students fail to form a positive attitude toward using them, even the most advanced technology cannot translate into actual learning effectiveness (Al-Hattami, 2023; Sung *et al*., 2016). To further elucidate the acceptance mechanism of vocational students toward AI teaching platforms, this study adopts a technology–task–attitude perspective to explain how the alignment between technological characteristics and learning tasks shapes student attitudes (Al-Hattali *et al*., 2024; Sheng & Xiao, 2022).

To explain technology acceptance behavior, the technology acceptance model (TAM) is widely recognized as a core theoretical framework for predicting user attitudes toward new technologies (Davis, 1989; Granić & Marangunić, 2019). In TAM, perceived usefulness is a key determinant of attitude toward using and behavioral intention (Davis, 1989). However, traditional TAM focuses on individual cognitive perceptions and often overlooks the alignment between technological characteristics and specific task requirements (Chaudhry *et al*., 2023). In the project-oriented curriculum of vocational computer majors, learning tasks are characterized by complex toolchains, dynamic contexts, and explicit output requirements. This makes the fit between technology and tasks a potentially more direct antecedent of attitude formation (Pan *et al*., 2016; Huang, 2024). Task-technology fit (TTF) complements this perspective as a key antecedent (Widodo *et al*., 2022). TTF emphasizes the degree of alignment between technological capabilities and task requirements. Higher fit allows students to perceive the technology as instrumental in completing specific learning tasks, thereby enhancing perceived usefulness and stimulating positive attitudes (Dishaw & Strong, 1999; Isaac *et al*., 2019; Soodan *et al*., 2024).

Although numerous studies have explored TAM in educational technology (Cheung & Vogel, 2013; Sánchez-Prieto *et al*., 2016), current literature presents two notable limitations. First, previous studies have predominantly focused on general undergraduate universities or general student populations, paying less attention to computer majors in higher vocational colleges—a group with distinct career-oriented characteristics (Cao *et al*., 2023; Popenici & Kerr, 2017). Second, regarding emerging AI teaching platforms, few studies have thoroughly investigated the specific pathway through which task-technology fit shapes student attitudes by influencing perceived usefulness (Osman & Yatam, 2024).

To bridge these gaps, this study grounds its theoretical foundation in the Technology acceptance model and integrates task-technology fit as a key external variable to construct an integrated research model (Davis, 1989; Goodhue & Thompson, 1995). This study aims to investigate the structural relationships among task-technology fit, perceived usefulness, and attitude toward using AI teaching platforms among computer majors in higher vocational colleges (Sun *et al*., 2023). The findings provide empirical evidence and managerial implications for optimizing the design of vocational education AI platforms and enhancing student technology acceptance (Al-Mamary *et al*., 2024).

2 LITERATURE REVIEW AND HYPOTHESIS DEVELOPMENT

2.1 Technology acceptance model

Fishbein and Ajzen's (1975) theory of reasoned action (TRA) posits that behavioral intention is the primary predictor of behavior, and attitude is a key antecedent of intention. To better explain and predict information technology use, Davis (1985) proposed the technology acceptance model based on TRA and subsequently formalized its constructs and causal paths (Davis *et al*., 1989). The classic TAM posits that perceived usefulness (PU) and perceived ease of use (PEOU) shape attitude toward using (ATU) and behavioral intention, which in turn influence actual use (Davis *et al*., 1989; Venkatesh & Bala, 2008). Within TAM, PU typically shows stronger and more stable predictive power than PEOU for attitude and behavioral intention (Davis *et al*., 1989). In educational technology and other emerging-technology contexts, TAM is often extended with contextual external variables to improve its fit with real-world use scenarios (Legris *et al*., 2003; Abdullah *et al*., 2016; Marangunić & Granić, 2015).

With the rapid expansion of artificial intelligence technology in the education sector, TAM has been widely used to explain learners' acceptance processes regarding AI-related tools and platforms. Studies have repeatedly verified the critical roles of perceived usefulness and perceived ease of use in shaping attitude and usage-related outcomes (Granić & Marangunić, 2019; Scherer *et al*., 2019; Saif *et al*., 2024). When learners can clearly perceive the practical value of technology for learning support, perceived usefulness is more likely to translate into positive attitudes and usage tendencies; conversely, operational complexity and interface burdens may weaken related evaluations and inhibit usage (Zawacki-Richter *et al*., 2019; Al-Adwan *et al*., 2023).

Although TAM provides a clear psychological pathway for understanding technology acceptance, relying solely on general judgments of usefulness and ease of use may be insufficient to characterize the sources of variation in learners' attitude formation within the complex context of AI integration into professional learning (Marangunić & Granić, 2015; Al-Dokhny *et al*., 2024). Therefore, while retaining the key constructs of TAM, this study introduces task-technology fit as an external explanatory variable to strengthen the characterization of the matching mechanism between technological features and learning task requirements, thereby advancing subsequent hypothesis development (Goodhue & Thompson, 1995; Venkatesh & Bala, 2008).

2.2 Task-technology fit and perceived usefulness

TTF refers to the degree to which learners perceive that an AI teaching platform’s functional characteristics match their learning task requirements (e.g., programming practice and project-based inquiry). It emphasizes users’ subjective sense of fit during task completion (Yuce *et al*., 2019). PU is defined as the extent to which an individual believes that using a particular system would enhance job or learning performance (Davis, 1989). For students in higher vocational computer majors, PU may be reflected in their beliefs that an AI teaching platform can improve coding efficiency, streamline problem-solving, and enhance academic performance (Revythi & Tselios, 2019).

The alignment between technological functions and task requirements is often a prerequisite for forming usefulness perceptions (Goodhue & Thompson, 1995). When technology responds well to task demands, users experience lower cognitive load, enabling them to focus more on core learning activities and perceive the technology's instrumental value (Dishaw & Strong, 1999). In AI-supported teaching, Al-Maatouk *et al*. (2020) reported that closer alignment between intelligent tools and academic tasks is associated with substantially higher usefulness evaluations. Similarly, Soodan *et al*. (2024) found that for AI chatbots, high fit indicates that the technology addresses specific pain points effectively; this problem–solution alignment strengthens users' perceived value of the technology. By contrast, when platform functions are misaligned with course tasks, learners may struggle to convert system capabilities into tangible learning gains, which undermines PU (Dishaw & Strong, 1999; Goodhue & Thompson, 1995). Accordingly, the following hypothesis is proposed:

H1: Task-technology fit has a significant positive effect on perceived usefulness.

2.3 Perceived usefulness and attitude toward using

ATU is defined as an individual's positive or negative evaluation and affective tendency toward using a specific technology (Davis, 1989). In this study, ATU is operationalized as students' positive or negative feelings and evaluations formed while using an AI teaching platform (Moon & Kim, 2001). ATU thus reflects both learners' value judgments and their affective experience during human–technology interaction (Davis, 1989; Moon & Kim, 2001).

Within TAM, PU is a central determinant of attitude: when learners believe a technology improves performance, they are more likely to develop a positive attitude toward using it (Davis, 1989). For higher vocational computer students facing complex skill-learning tasks, a pragmatic orientation is often more salient (Venkatesh & Davis, 2000). When students find that an AI platform supports demanding project-based practical training effectively, perceived utility can translate into trust and liking for the platform, fostering a positive attitude (Fathema & Akanda, 2020). In high-complexity learning environments, PU may also promote positive attitudes by strengthening psychological resources such as self-efficacy (Lai, 2017; Hu *et al*., 2022). Thus, the following hypothesis is proposed:

H2: Perceived usefulness has a significant positive effect on attitude toward using.

2.4. Task-technology fit and attitude toward using

Goodhue (1998) noted that higher task-technology fit can produce smoother user experiences, thereby reducing technology anxiety and supporting more positive attitudes. In educational technology research, Ojetunde *et al*. (2025) found that higher fit significantly reduces students' uncertainty and frustration when they encounter new technologies. Particularly when an AI teaching platform's feedback mechanisms closely align with students' inquiry tasks, the interaction can feel more fluent and less frustrating, which may foster a more positive attitude toward using the platform even without relying heavily on complex cognitive evaluations (Huang *et al*., 2024; Rabbani *et al*., 2024). Accordingly, the following hypothesis is proposed:

H3: Task-technology fit has a significant positive effect on attitude toward using.

2.5 Research model and hypotheses

This study examines how TTF influences ATU among higher vocational computer-major students in the context of AI integration into teaching. Figure 1 presents the research model, which includes three core variables: TTF, PU, and ATU. TTF is posited as a key antecedent. The model tests TTF's direct effects on PU and ATU, as well as PU's effect on ATU, forming the structural relationships examined in this study.

Based on the above arguments, the hypotheses are summarized as follows:

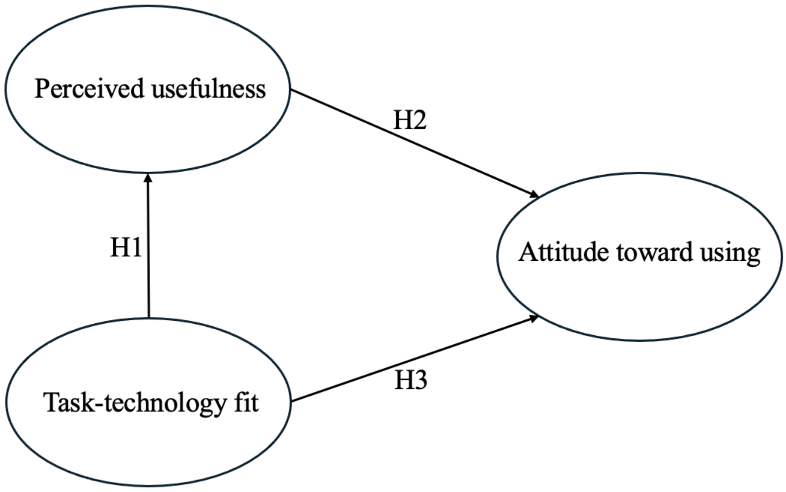
H1: Task-technology fit has a significant positive effect on perceived usefulness.

H2: Perceived usefulness has a significant positive effect on attitude toward using.

H3: Task-technology fit has a significant positive effect on attitude toward using.

Figure 1

Research Framework.



3 METHODOLOGY

3.1 Participants and data collection

This study relies on the Intelligent Cloud Vocational Education Platform (iCVE), which provides functions such as resource sharing, learning support, and learning process management (e.g., intelligent recommendation and learning path customization), thereby offering a relatively standardized technological interaction environment for students. Given the high dependence of computer-related courses on information technology and the relatively clear structure of their learning tasks, this study focused on students majoring in computer-related fields at higher vocational colleges in Hunan Province. To ensure contextual consistency and minimize confounding due to cross-major differences in task characteristics, only students whose core professional courses and practical training had relied heavily on iCVE for at least one semester were included.

To ensure sample representativeness and control sampling error, this study employed stratified two-stage sampling (Kish, 1965; Lohr, 2021). The first stage used colleges as the sampling unit, and the second stage involved sampling students within the selected colleges. Stratification was based on the number of colleges offering computer-related majors at the municipal or prefectural level, to ensure coverage across regions with different levels of college concentration.

In the first stage (college sampling), 58 colleges were divided into three strata: high-density (24 colleges, 41.38%), medium-density (18 colleges, 31.03%), and low-density (16 colleges, 27.59%). Within each stratum, systematic sampling was employed to select colleges in proportion to stratum size, resulting in the selection of 10, 6, and 4 colleges, respectively, for a total of 20 colleges.

In the second stage (student sampling), given that first-year students primarily take general education courses and are less likely to engage in intensive use of professional platforms, this study limited the within-college sample to second- and third-year students. Within each selected college, students were first stratified by year level, after which simple random sampling was conducted within each year-level stratum based on the student roster in the iCVE backend system. Twenty students were selected from each year level (40 students per college), and a total of 800 questionnaires were distributed. Ultimately, 716 valid responses were obtained, yielding an effective response rate of 89.5%. Questionnaires were administered through a combination of centralized in-class administration and online distribution via platform links, with course instructors assisting in participant briefing and reminders.

3.2 Measures

To ensure the reliability and validity of the measurements, this study utilized established scales widely used in international journals. To guarantee linguistic accuracy and cross-cultural applicability, the standard translation-back-translation procedure suggested by Brislin (1970) was followed. First, two bilingual experts translated the original English scales into Chinese, and then two other scholars who had not seen the original scales translated the Chinese version back into English. Through comparing the conceptual equivalence between the back-translated version and the original scales, multiple rounds of wording revisions were conducted to form the final formal scales.

Task-technology fit scale: This study adopted the scale by Yuce *et al*. (2019) to measure students' perception of task-technology fit. The items in this scale possess generality and flexibility, effectively adapting to the "task-technology" interaction context focused on in this study. It is used to measure the degree of match perceived by students between the platform's functional characteristics and the learning tasks of computer majors. The scale demonstrated good reliability and validity (Cronbach's Alpha = 0.905, CR = 0.901, AVE = 0.533) (Yuce *et al*., 2019).

Perceived usefulness scale: This study employed the scale revised by Revythi and Tselios (2019), based on TAM and combined with SUS concepts. It captures students' comprehensive perception of the overall utility and user experience of e-learning tools, thereby better reflecting learners' overall judgment of the pragmatic value of such tools (Borsci *et al*., 2022; Zwakman *et al*., 2021). The Cronbach's Alpha of this scale was greater than 0.850, and factor analysis verified its structural validity (Revythi & Tselios, 2019).

Attitude toward using scale: Considering the similarity between the application context of AI technology in learning environments and the World Wide Web application environment, and given that the Technology acceptance model effectively explains the formation mechanism of technology usage attitudes, this study chose to adapt the scale from Moon and Kim (2001) as the tool to measure attitude toward using. This scale extends the traditional TAM theory to the WWW environment and incorporates factors such as user experience and satisfaction with network functions. It showed good reliability (Cronbach's Alpha=0.905) and validity, enabling a more comprehensive capture of users' true attitudes in complex technology usage contexts, making it suitable for measuring platform usage attitude in this study (Kim, 2023; Su, 2022; Suh & Ahn, 2022; Tarhini *et al*., 2015).

3.3 Data analysis methods

This study employed quantitative analysis methods, using IBM SPSS Statistics for descriptive statistics and reliability analysis, and IBM SPSS Amos for Confirmatory Factor Analysis (CFA) and Structural Equation Modeling (SEM) analysis.

(1) Descriptive statistics and normality checks

First, SPSS was used to conduct frequency analysis on the demographic characteristics of the sample (e.g., gender, grade). Second, the mean, standard deviation, skewness, and kurtosis of each construct (TTF, PU, ATU) were calculated to test the normality of univariate distributions. According to Kline's (2023) empirical thresholds, if the absolute value of skewness is less than 3 and the absolute value of kurtosis is less than 10, the data can be considered to approximately satisfy the normality requirement, making it suitable for subsequent model analysis using Maximum Likelihood Estimation.

(2) Reliability analysis

Cronbach's Alpha was used to assess internal consistency, combined with Corrected Item–Total Correlation (CITC) to judge the fit between items and constructs. Generally, a Cronbach's Alpha ≥ 0.700 indicates good internal consistency; if the CITC of individual items is significantly low, removal will be carefully evaluated combining theoretical implications and statistical results to enhance the measurement stability of the scale (Nunnally & Bernstein, 1994).

(3) Measurement model assessment

Following the two-stage analysis procedure recommended by Anderson and Gerbing (1988), the measurement model's fit and validity were first assessed via CFA before proceeding to structural model testing. Convergent validity testing includes: standardized factor loadings of items being significant and ideally not lower than 0.500 (more ideally ≥ 0.700), Composite Reliability (CR) ≥ 0.700, and Average Variance Extracted (AVE) ≥ 0.500. Discriminant validity was assessed using the Fornell–Larcker criterion, which requires that the square root of the AVE for each construct be greater than its correlation coefficients with other constructs (Fornell & Larcker, 1981).

(4) Structural model assessment

Premised on acceptable measurement model fit, the structural model was further tested and path coefficients were estimated to examine H1–H3. The model fit report will present key fit indices commonly used in structural equation modeling research, including χ^2/df, CFI, TLI, RMSEA, and SRMR, to assess the degree of match between the model and the data.

4 RESULTS

4.1 Sample profile

The formal survey questionnaires were distributed and collected through a combination of centralized classroom administration and targeted distribution via the iCVE platform. A total of 800 questionnaires were distributed to second- and third-year students majoring in computer-related fields across 20 sample colleges in Hunan Province, with 757 returned, yielding a response rate of 94.6%. To ensure data quality, data cleaning and screening were conducted based on criteria such as incomplete responses, abnormal response duration, and straightlining or patterned responding (DeSimone & Harms, 2018; Hair *et al*., 2010). Ultimately, 41 invalid questionnaires were excluded, resulting in 716 valid questionnaires, with an effective response rate of 89.5%.

The demographic characteristics of the sample are shown in Table 1. In terms of gender distribution, there were 376 male students (52.51%) and 340 female students (47.49%), indicating a balanced gender ratio. Regarding grade distribution, second-year students accounted for 48.60%, while third-year students accounted for 51.40%. The sample structure is reasonably balanced and appears broadly representative of the surveyed population.

Table 1

Sample demographics

Variable	Category	N	Percentage %
Gender	Male	376	52.51%
	Female	340	47.49%
Grade	Year 2	348	48.60%
	Year 3	368	51.40%

4.2 Descriptive statistics and normality test

This study first examined the descriptive statistics and distributional characteristics of each latent variable. As shown in Table 2, the means for perceived usefulness, task-technology fit, and attitude toward using were 3.163, 4.987, and 3.339, respectively. The normality test results indicated that the skewness for all constructs ranged from -1.035 to -0.172, and the kurtosis ranged from -0.793 to 1.565. All indicators complied with the threshold standards suggested by Kline (2023), i.e., the absolute value of skewness being less than 3 and the absolute value of kurtosis being less than 10. The research data did not show severe deviation from normal distribution at the univariate level, supporting the use of maximum likelihood estimation (MLE) in subsequent analyses. Furthermore, to further enhance the robustness of statistical inference and correct for potential distribution biases, this study employed bootstrapping with 5,000 resamples to obtain standard errors and confidence intervals in the subsequent structural equation modeling analysis.

Table 2

Descriptive statistics of the constructs

Construct	N	Min.	Max.	Mean	SD	Skewness	Kurtosis
PU	716	1	5	3.163	0.995	-0.185	-0.793
TTF	716	1	7	4.987	1.105	-1.035	1.565
ATU	716	1	5	3.339	1.020	-0.172	-0.791

4.3 Measurement model assessment

This study first conducted a Confirmatory Factor Analysis on the measurement model comprising task-technology fit, perceived usefulness, and attitude toward using. To facilitate comparability, standardized estimates are reported to interpret loadings and correlations on the same scale. The CFA results showed that the measurement model fitted the data well (χ^2/df = 1.129, CFI = 0.999, TLI = 0.998, RMSEA = 0.013, SRMR = 0.018), indicating that the measurement model has acceptable overall fit.

Subsequently, the reliability and convergent validity of the measurement model were tested. As shown in Table 3, the Standardized Factor Loadings for all measurement items ranged from 0.756 to 0.917, and all reached statistical significance ($p < 0.001$), exceeding the recommended threshold of 0.700. The Cronbach's alpha coefficients and Composite Reliability (CR) for each construct were all greater than 0.700, indicating good internal consistency of the scales. Meanwhile, the Average Variance Extracted (AVE) for all constructs was higher than 0.500, supporting that the measurement model possesses good convergent validity.

Table 3

Measurement model assessment

Construct	Item	Factor Loading	Cronbach's Alpha	CR	AVE
Perceived usefulness	PU1	0.856	0.894	0.894	0.679
	PU2	0.792			
	PU3	0.784			
	PU4	0.861			
Task-technology fit	TTF1	0.809	0.898	0.899	0.641
	TTF2	0.798			
	TTF3	0.756			
	TTF4	0.814			
	TTF5	0.823			
Attitude toward using	ATU1	0.814	0.927	0.927	0.762
	ATU2	0.842			
	ATU3	0.917			
	ATU4	0.914			

Finally, this study assessed discriminant validity according to the Fornell-Larcker criterion. As shown in Table 4, the bold values on the diagonal represent the square root of the AVE for each construct (0.801 - 0.873), which are all greater than the correlation coefficients between that construct and other constructs (0.478 - 0.572). Therefore, discriminant validity was supported.

Table 4

Discriminant validity (Fornell-Larcker Criterion)

	PU	TTF	ATU
PU	**.824**		
TTF	.572	**.801**	
ATU	.502	.478	**.873**

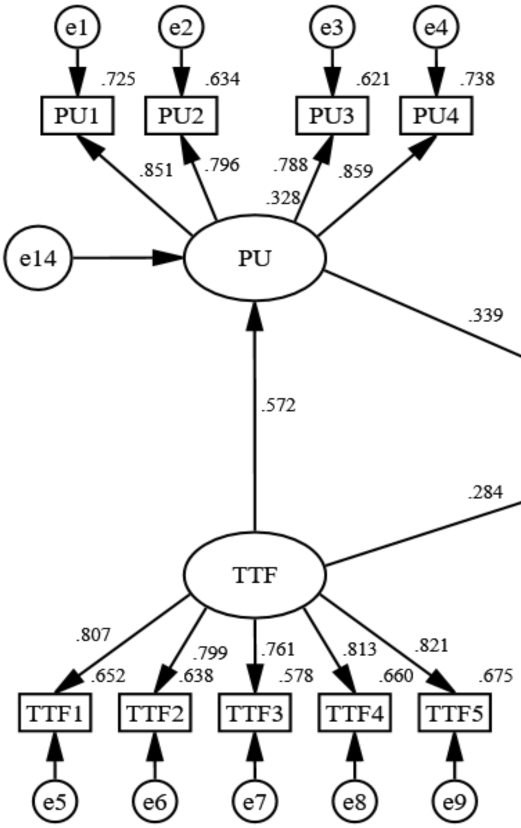
Note: Bold values on the diagonal represent the square root of AVE; off-diagonal values are correlations between constructs.

4.4 Structural model assessment and hypothesis testing

Based on the measurement model demonstrating acceptable reliability and validity, this study constructed a structural equation model to test the hypothesized path relationships of H1 to H3. The structural model is shown in Figure 2.

Figure 2

Overall Structural Model



4.4.1 Model fit indices

The overall fit indices of the structural model are shown in Table 5. The results indicated that $\chi^2 = 70.026$ (df = 62, $p = 0.226$), χ^2/df = 1.129, CFI = 0.999, TLI = 0.998, RMSEA = 0.013, and SRMR=0.018. All key fit indicators reached or exceeded the fit standards recommended by Hair *et al*. (2010), indicating that the structural model fits the sample data well, the model structure is statistically reasonable, and it is suitable for further testing the hypothesized paths.

Table 5

Model fit indices

Index	**χ^2**	***p***	**χ^2/df**	**SRMR**	**RMSEA**	**TLI**	**CFI**
Value	70.026	0.226	1.129	0.018	0.013	0.998	0.999

4.4.2 Path estimates and hypothesis testing

The path coefficients and hypothesis testing results are summarized in Table 6. Data analysis showed that:

First, task-technology fit has a significant positive effect on perceived usefulness ($B = 0.574$, $\beta = 0.572$, $p < 0.001$), supporting hypothesis H1.

Second, perceived usefulness significantly and positively predicts attitude toward using ($B = 0.318$, $\beta = 0.339$, $p < 0.001$), supporting hypothesis H2.

Third, task-technology fit also demonstrates a significant direct positive effect on attitude toward using ($B = 0.266$, $\beta = 0.284$, $p < 0.001$), supporting hypothesis H3.

To test the robustness of the parameter estimates, this study used bootstrapping with 5,000 resamples to compute bias-corrected 95% confidence intervals. The results showed that the confidence intervals for all three paths did not include 0, further verifying the reliability of the above hypothesis testing results.

Table 6

Structural model path coefficients

Hypothesis	Path	*B*	S.E.	C.R.	*β*	95% CI
H1	TTF→PU	0.574	0.041	14.034***	0.572	[0.487, 0.665]
H2	PU→ATU	0.318	0.043	7.356***	0.339	[0.218, 0.427]
H3	TTF→ATU	0.266	0.043	6.188***	0.284	[0.176, 0.365]

Note: ***p<0.001; Bias-corrected 95% confidence intervals were obtained using 5,000 bootstrap resamples.

5 DISCUSSION

5.1 The relationship between students' task-technology fit and perceived usefulness

The structural model results showed a significant positive relationship between task-technology fit and perceived usefulness ($\beta = 0.572$, $p < 0.001$), supporting hypothesis H1. This result indicates that for computer-major students in higher vocational colleges in Hunan Province, their perception of the degree of match between iCVE platform functions and professional learning tasks is a significant antecedent of usefulness evaluations. This finding is consistent with Dishaw and Strong’s (1999) argument that task-technology fit can reinforce usefulness perceptions. Specifically in the context of this study, computer-related professional courses typically involve tasks such as code writing, practical operations, and project-based practical training, characterized by highly structured, hands-on work. When the AI-assisted functions provided by the iCVE platform adequately address these specific task requirements, students may experience lower technical friction and cognitive load when completing tasks. Such a smoother task processing experience may further reinforce students’ recognition of the platform’s instrumental value (Al-Maatouk *et al.*, 2020). Overall, in skill-output-oriented professional learning, learners’ judgment of usefulness often depends more on whether platform functions can effectively support the completion of specific disciplinary tasks.

5.2 The relationship between students' perceived usefulness and attitude toward using

The structural model results indicated a significant positive relationship between perceived usefulness and attitude toward using ($\beta = 0.339$, $p < 0.001$), supporting hypothesis H2. This suggests that when learners perceive greater usefulness of AI integration into teaching, they are more likely to hold a positive attitude toward using the platform. This conclusion aligns with the views of Venkatesh and Davis (2000) and Teo (2011) that, as technological complexity increases, users tend to place greater emphasis on practical utility.

In the present context, “usefulness” primarily refers to the extent to which students believe that the platform helps them achieve learning goals more effectively—such as improving learning efficiency, enhancing task performance, and ultimately supporting better academic outcomes. When students perceive clear, performance-relevant benefits from AI-assisted learning (e.g., faster completion of learning tasks, more effective problem solving, or improved learning results), they are more likely to evaluate the platform favorably and develop a positive attitude toward continued use. This result suggests that, in vocational education settings characterized by skill-oriented learning, making the platform's contribution to learning performance salient and verifiable may be a key lever for fostering positive attitudes.

5.3 The relationship between students' task-technology fit and attitude toward using

The structural model results showed a significant positive relationship between task-technology fit and attitude toward using ($\beta = 0.284$, $p < 0.001$), supporting hypothesis H3. Goodhue and Thompson (1995) pointed out that the degree of fit between technology and task requirements is a key factor influencing user experience. Du *et al.*'s (2024) research also suggests that under conditions of high technology fit, learners are more likely to accept and be willing to use new learning technologies long-term. The results of this study further support these views. This means that when the functional design of the AI teaching platform fully considers the specificities of computer major courses, such as practical training operations and logical verification, and aligns well with students’ learning tasks, students may experience lower frustration and technical friction, thereby being more likely to form a positive attitude toward using. When technology acts more like a tool facilitating learning rather than an extra burden, learners’ attitude toward using is more likely to be enhanced, as reflected in higher willingness to participate.

6 CONCLUSION

6.1 Research conclusion

This study empirically tested the structural relationships among task-technology fit, perceived usefulness, and attitude toward using through structural equation modeling. Based on the analysis of survey data from computer-major students in higher vocational colleges in Hunan Province, three main conclusions were drawn.

First, task-technology fit has a significant positive relationship with perceived usefulness, indicating that it may be an important predictor of perceived usefulness. The results show that when the functional characteristics provided by the iCVE platform closely match the highly structured learning task requirements of computer majors, students’ perception of the instrumental value of the technology may be more prominent. This result supports the critical role of task-technology fit in the formation of learners’ value judgments.

Second, perceived usefulness has a significant positive relationship with attitude toward using, indicating that higher perceived usefulness is typically accompanied by a more positive attitude toward using. The study shows that higher vocational computer students exhibit distinct pragmatic characteristics in technology adoption behavior. Students’ acceptance of AI teaching tools depends largely on whether they can tangibly improve learning efficiency or optimize practical training outcomes; this utility-based assessment is a key mechanism driving the formation of positive attitudes.

Third, task-technology fit has a significant direct effect on attitude toward using, indicating that fit remains related to attitude even after controlling for perceived usefulness. A smooth task processing experience and low-friction technical interaction can directly reduce students' psychological resistance, thereby strengthening their acceptance of AI-supported teaching. In summary, the results of this study support the direct effect of task-technology fit on attitude toward using, and are consistent with the proposed structural relationships among task-technology fit, perceived usefulness, and attitude toward using.

6.2 Practical implications

Based on the above conclusions, this study provides the following practical suggestions for educational administrators and technology developers in higher vocational colleges.

First, platform developers should prioritize task-specific feature design. They should not pursue generic "AI functions" by default, they should start from core computing tasks (e.g., debugging, system maintenance, project-based practice) and design tools that directly reduce task friction and improve task completion.

Second, educators should implement AI tools through problem-solving demonstrations. When introducing the platform, teachers are advised to show concrete performance gains (e.g., higher efficiency, better troubleshooting, improved outputs). Use authentic, project-based cases so students can experience usefulness through real problem solving.

Third, instructional administrators should align course tasks with platform affordances. It is advisable to reduce low-challenge uses (e.g., attendance-only, simple Q&A). Assign inquiry-based tasks that require meaningful human–AI collaboration, so students can experience successful task completion and sustain continued use.

6.3 Limitations and future research

Although this study strived for rigor in theoretical construction and empirical analysis, the following objective boundary conditions must be considered when interpreting the results, which also point out directions for future research.

First, the cross-sectional data limit strict causal inference. This study employed a cross-sectional design to capture the structural relationships between students' task-technology fit and attitude at a specific point in time. Although structural equation modeling statistically verified strong association paths between variables, it is difficult to completely rule out potential bidirectional interactions or dynamic evolutionary processes among variables. Future research could employ longitudinal tracking designs or cross-lagged analysis to more precisely characterize the time-lag effects and causal dynamics of fit on attitude.

Second, the selection of a specific technological context constrains the scope of applicability for the research conclusions. To control for confounding variables caused by differences in the technical architecture of different teaching platforms, this study limited the survey scope to computer-related majors in Hunan Province that uniformly use the iCVE platform. While this choice of a homogeneous context ensured internal validity, it also limits the direct generalization of conclusions to other platforms or non–skills-oriented majors. Future research could conduct cross-regional or cross-platform comparative studies to test the generalizability of the structural relationship model proposed in this study across different educational technology ecosystems.

Third, the study relies on subjective self-report data, which constitutes a limitation. The core variables of this study were all measured based on student self-report scales. Although corresponding measures were taken during the research design phase to reduce the risk of potential measurement bias, such data still primarily reflect learners' subjective perceptions and are difficult to directly represent their actual usage behavior. Future research could further integrate platform backend behavioral data, such as login frequency, task completion duration, and practical training scores, as objective indicators for cross-validation with perceptual variables. This would enhance the external validity and ecological validity of the research conclusions and support a more multidimensional model of technology acceptance and usage behavior.

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Authors' Contribution

All authors contributed equally to the development of this article.

Data availability

All datasets relevant to this study's findings are fully available within the article.

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