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Digital Competence and Teaching Innovation in Vietnamese Higher Education: The Mediating Role of Artificial Intelligence Acceptance

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ABSTRACT: Digital competence and artificial intelligence (AI) acceptance shape the extent to which technology can be translated into pedagogical innovation. This study examines the levels of the three constructs, their direct effects, and the mediating role of AI acceptance. Survey data from 386 university lecturers were analysed using SPSS 27 through Cronbach's alpha, exploratory factor analysis (EFA), correlation analysis, regression analysis, and PROCESS Model 4. The results show that digital competence positively predicts AI acceptance and teaching innovation; AI acceptance is the stronger predictor and partially mediates the relationship. The study recommends discipline-specific, scenario-based professional development, controlled experimentation with AI, and guidelines for responsible AI use.

KEYWORDS: Digital competence, artificial intelligence acceptance, teaching innovation, university lecturers, higher education.

1. INTRODUCTION

Artificial intelligence (AI), particularly generative AI, is increasingly being integrated into university teaching. This technology enables lecturers to design learning materials, provide feedback, and personalise learning tasks. However, access to technological tools does not necessarily translate into pedagogical innovation. Such benefits can only be realised when lecturers possess digital competence, understand the limitations of AI, verify its outputs, and align its use with learning objectives.

According to DigCompEdu, educators' digital competence encompasses the management of digital resources, the organisation of teaching and learning, assessment, and learner support (Redecker, 2017). Beyond competence, the decision to use AI also depends on perceived usefulness, perceived ease of use, confidence, and facilitating conditions, as explained by the Technology Acceptance Model (TAM) and the Unified Theory of Acceptance and Use of Technology (UTAUT) (Davis, 1989; Venkatesh et al., 2003). Recent studies have associated confidence, readiness, self-efficacy, outcome expectations, and environmental factors with lecturers' intentions to adopt AI (Liu, 2025; Xiang et al., 2025), while digital information competence and AI literacy have been linked to innovative teaching practices (Sarango-Lapo et al., 2021; Zhao & Huang, 2025).

In Vietnam, the relationships among digital competence, AI acceptance, and teaching innovation among university lecturers have not been comprehensively tested within an integrated model. Accordingly, this study assesses the levels of the three constructs, examines their direct relationships, and investigates the mediating role of AI acceptance.

2. RESEARCH CONTENT

2.1. Theoretical background

2.1.1. Digital competence among university lecturers

Lecturers' digital competence refers to their ability to mobilise knowledge, skills, attitudes, and professional judgement in using technology for teaching, research, and professional development. DigCompEdu organises this competence into six areas that connect technological practices with pedagogical tasks (Redecker, 2017). In this study, digital competence is measured through digital resource management; instructional design and delivery; assessment and feedback; and responsible AI use.

Digital competence depends on context and conceptions of teaching. Dias-Trindade and Albuquerque (2022) examined differences by gender, age, faculty, and teaching experience but found no statistically significant differences; they suggested that professional development should focus on weaker areas of competence within DigCompEdu. Mirete et al. (2020) investigated the relationship between digital competence and university lecturers' conceptions of teaching. Thus, professional development should situate technological tools within discipline-specific teaching scenarios rather than focusing exclusively on operational skills.

AI extends digital competence to include the ability to formulate prompts, verify accuracy, identify bias, protect data, and determine which tasks should not be delegated to machines. UNESCO advocates a human-centred approach that emphasises privacy, ethical assessment, and pedagogical design (Miao & Holmes, 2023).

2.1.2. Artificial intelligence acceptance

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AI acceptance reflects the extent to which lecturers perceive the technology as useful, usable, and worth integrating into their practice. TAM explains the roles of perceived usefulness and perceived ease of use (Davis, 1989), while UTAUT additionally incorporates social influence and facilitating conditions (Venkatesh et al., 2003). In the context of AI, acceptance also involves control over outputs, ethical risks, and academic standards.

AI acceptance is not a single-dimensional response. Liu (2025) showed that AI confidence and AI readiness act as separate and sequential mediators between subjective norms and behavioural intention to use AI. Xiang et al. (2025) highlighted the roles of self-efficacy, outcome expectations, and environmental factors in intentions to adopt AI-generated content (AIGC) for teaching. This study measures acceptance in terms of perceived usefulness, ease of use, confidence, and intention to integrate AI into teaching.

2.1.3. Teaching innovation

Sarango-Lapo et al. (2021) linked digital information competence to evidence-based innovation practices. Zhao and Huang (2025) likewise found that AI literacy is associated with teaching innovation through psychological mechanisms. On this basis, this study measures innovation through the development of new learning materials and tasks; personalisation; innovative interaction and feedback; assessment adaptation; experimentation with new methods; and the redefinition of lecturers' roles in AI-enabled environments.

2.1.4. Relationships among the constructs and the research gap

Four hypotheses are proposed based on the literature review. H1: Digital competence positively influences AI acceptance because relevant skills reduce perceived effort, facilitate recognition of benefits, and support risk management. H2: Digital competence positively influences teaching innovation by expanding the range of options for instructional design and assessment. H3: AI acceptance positively influences teaching innovation because positive beliefs and confidence encourage experimentation. H4: AI acceptance mediates the relationship between digital competence and teaching innovation; in other words, competence is translated into behaviour partly through positive evaluations and intention to use AI.

Table 1. Proposed constructs and measurement scales

Construct	Code	Items	Measurement domains
Digital competence	DC	12	Digital resources; instructional design; assessment and feedback; responsible AI use
AI acceptance	AA	8	Perceived usefulness; perceived ease of use; confidence; intention to integrate AI
Teaching innovation	TI	8	New learning materials and tasks; personalisation; interaction and feedback; assessment; experimentation with methods

Source: Compiled and adapted by the authors from published studies.

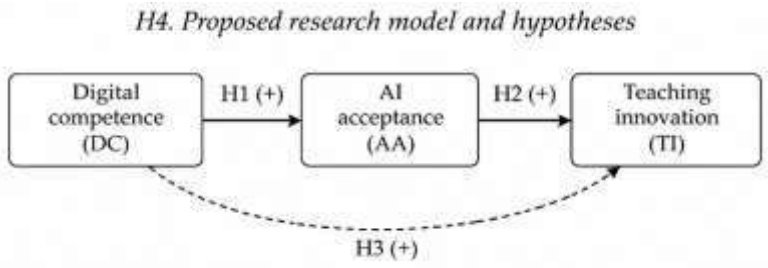

Figure 1. Proposed research model
Source: Proposed by the authors.

2.2. Research model and hypotheses

The model comprises three latent constructs: digital competence (DC), AI acceptance (AA), and teaching innovation (TI). Four hypotheses are tested: H1, DC positively influences AA; H2, DC positively influences TI; H3, AA positively influences TI; and H4, AA mediates the relationship between DC and TI. Mediation is tested using PROCESS Model 4 (Hayes, 2022), with 5,000 bootstrap samples and a 95% confidence interval.

2.3. Research methodology

2.3.1. Research design, sample, and data

The study adopts a cross-sectional quantitative research design based on survey data. The research process comprises a literature review, the development of the research model and measurement scales, data collection, and hypothesis testing. A total of 450 questionnaires were distributed, 412 were returned, and 386 valid responses were obtained from 12 higher education institutions. All observed variables were measured using a five-point Likert scale.

2.3.2. Analytical tools and procedures

The data were analysed using SPSS 27. Internal consistency was assessed using Cronbach's alpha, and exploratory factor analysis (EFA) was performed using principal axis factoring with Promax rotation. Reference thresholds were an alpha coefficient of at least 0.70, item–total correlations of at least 0.30, a Kaiser–Meyer–Olkin (KMO) value of at least 0.50, Bartlett's test $p < 0.05$, preferred factor loadings of at least 0.50, and explained variance of at least 50%. Following EFA, composite mean scores were calculated, and Pearson correlation and linear regression analyses were conducted.

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The mediating role was examined using PROCESS Model 4 (Hayes, 2022), with 5,000 bootstrap samples and a 95% confidence interval. Multicollinearity was assessed through variance inflation factors (VIFs), and the independence of residuals was examined using the Durbin–Watson statistic. Given the cross-sectional design, the term "effect" refers to a predictive relationship rather than establishing definitive causality.

To mitigate common method bias in field research, questionnaires should ensure anonymity, arrange item groups appropriately, and explain that there are no right or wrong answers. After data collection, Harman's single-factor test may be used as an initial diagnostic, while a more rigorous measurement model may be considered if confirmatory factor analysis (CFA) or structural equation modelling (SEM) is applied. These measures cannot fully eliminate self-report bias, but they can reduce the risk that relationships among constructs are inflated because the data originate from the same source and are collected at the same time.

Because of the cross-sectional design, "effect" in this article is used in the sense of a predictive relationship in a regression model and does not imply definitive causality. In empirical research, procedures should be established for informed consent, data confidentiality, and ethics approval where required by the institution.

Table 2. Sample characteristics (n = 386)

Characteristic	Category	Frequency	Percentage (%)
Gender	Male	181	46.9
	Female	205	53.1
Age	≤ 35	106	27.5
	36–45	168	43.5
	≥ 46	112	29.0
Teaching experience	< 5 years	64	16.6
	5–10 years	118	30.6
	11–20 years	135	35.0
	> 20 years	69	17.9
Discipline	STEM	121	31.3
	Social sciences and humanities	112	29.0
	Economics and management	89	23.1
	Other	64	16.6
Institution type	Public	301	78.0
	Non-public	85	22.0

Source: Survey data.

2.4. Research findings

2.4.1. Descriptive statistics, reliability, and EFA

The mean score for DC was 3.74 (SD = 0.61), compared with 3.68 (SD = 0.67) for AA and 3.71 (SD = 0.63) for TI. In the dataset, all three constructs scored above the midpoint of the scale. The small differences between their means suggest relatively similar overall levels of competence, acceptance, and innovation among lecturers. However, standard deviations ranging from 0.61 to 0.67 still reflect individual variation sufficient for correlation and regression analyses.

Cronbach's alpha coefficients were 0.917 for DC, 0.896 for AA, and 0.884 for TI. All corrected item–total correlations exceeded 0.50, and no items were removed. These relatively high coefficients, all below 0.95, indicate good internal consistency without suggesting excessive item redundancy. The KMO value for the 28 observed items was 0.923. Bartlett's test yielded $\chi^2(378) = 5681.42$, $p < 0.001$, confirming that the correlation matrix was suitable for factor analysis.

EFA extracted three factors with eigenvalues greater than 1, accounting for 68.27% of the total variance. Factor loadings ranged from 0.612 to 0.851, with no substantial cross-loadings. The items loaded onto the three expected constructs.

Table 3. Reliability, EFA, and correlations among constructs

Construct	M	SD	Alpha	Factor loadings	1	2	3
1. DC	3.74	0.61	0.917	0.664–0.843	1.000		
2. AA	3.68	0.67	0.896	0.641–0.851	0.638***	1.000	
3. TI	3.71	0.63	0.884	0.612–0.829	0.584***	0.667***	1.000

Note: KMO = 0.923; Bartlett's $\chi^2(378) = 5681.42$; $p < 0.001$; total variance explained = 68.27%; *** $p < 0.001$.

2.4.2. Correlations and regression results

All correlations were positive and statistically significant at $p < 0.001$. DC correlated with AA at $r = 0.638$ and with TI at $r = 0.584$, while AA correlated with TI at $r = 0.667$. These coefficients, all below 0.80, indicate that the three constructs are associated but remain distinct. The results support proceeding with regression and mediation analyses.

In the model predicting AA, DC had a coefficient of $B = 0.701$, $SE = 0.043$, $\beta = 0.638$, $t = 16.24$, $p < 0.001$. The model explained 40.7% of the variance in AA. Thus, a one-point increase in DC was associated with a predicted 0.701-point increase in AA. H1 was supported.

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The model predicting TI included DC and AA and yielded $R^2 = 0.487$, adjusted $R^2 = 0.484$, and $F(2, 383) = 181.82$, $p < 0.001$. DC was positively associated with TI ($B = 0.276$, $\beta = 0.267$, $p < 0.001$), as was AA ($B = 0.467$, $\beta = 0.497$, $p < 0.001$). Comparison of the standardised beta coefficients indicates that AA was the stronger predictor in the same model. The VIF for both predictors was 1.69 and the Durbin–Watson statistic was 1.94, providing no indication of substantial multicollinearity or residual autocorrelation. H2 and H3 were supported.

2.4.3. Testing the mediating role

PROCESS Model 4 indicated that the total effect of DC on TI was $B = 0.603$, $SE = 0.043$, $p < 0.001$. After AA was included in the model, the direct effect declined to $B = 0.276$ but remained statistically significant. The indirect effect through AA was 0.327, BootSE = 0.043, with a 95% confidence interval of [0.246, 0.413]. Because the interval did not include zero, the mediation effect was statistically significant. AA partially mediated the relationship between DC and TI; H4 was supported.

The indirect effect represented approximately 54.2% of the total effect. In these survey data, more than half of the predictive relationship between digital competence and teaching innovation was transmitted through AI acceptance. This does not negate the direct pathway: digital competence may also facilitate lecturers' innovation through other digital technologies and practices, not solely AI.

Table 4. Regression and mediation analysis results

Relationship	B	SE	β / Effect	t	p / 95% CI	Result
DC → AA (a)	0.701	0.043	0.638	16.24	< 0.001	H1
DC → TI (c, total)	0.603	0.043	-	14.02	< 0.001	Significant
DC → TI (c′, direct)	0.276	0.044	0.267	6.27	< 0.001	H2
AA → TI (b)	0.467	0.040	0.497	11.68	< 0.001	H3
DC → AA → TI	-	0.043	0.327	-	[0.246, 0.413]	H4

Note: Bootstrap = 5,000 samples; 95% confidence interval.

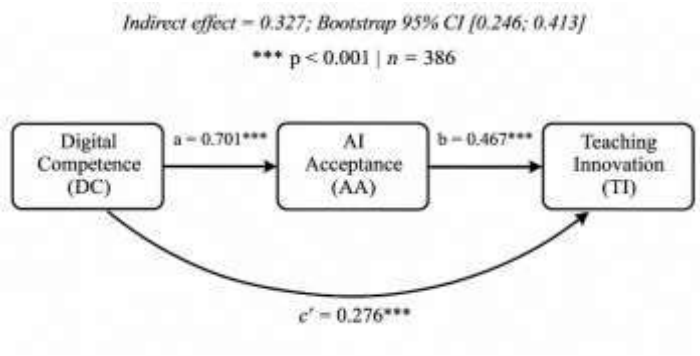

Figure 2. Results of the mediation model
Source: Results of the survey data analysis.

2.5. Discussion

The positive association between DC and AA can be interpreted in light of TAM and UTAUT, which emphasise the roles of perceived usefulness, perceived ease of use/effort expectancy, social influence, and facilitating conditions in technology acceptance (Davis, 1989; Venkatesh et al., 2003). In practice, successful experimentation may transform technical knowledge into evidence-based confidence.

Digital competence also directly predicts teaching innovation, consistent with studies linking digital competence to conceptions of teaching (Mirete et al., 2020) and digital information competence to evidence-based educational innovation practices (Sarango-Lapo et al., 2021). Competence broadens lecturers' repertoire of solutions for redesigning learning resources, feedback, and assessment; the value of innovation lies in pedagogical processes rather than the number of tools used.

AI acceptance was the stronger predictor in the model. Possessing competence does not necessarily imply readiness to act if lecturers question the reliability of AI, lack guidance, or perceive substantial risks. This finding is consistent with research on confidence, readiness, and outcome expectations in AI adoption (Liu, 2025; Xiang et al., 2025).

The mediation effect indicates that digital competence predicts innovation both directly and through AI acceptance. This finding is broadly consistent with Zhao and Huang (2025), who found that AI literacy promotes teaching innovation through behavioural attitudes, subjective norms, and perceived behavioural control. Future field research in Vietnam should additionally examine organisational support, teaching autonomy, ethical concerns, disciplinary characteristics, and actual patterns of use.

2.6. Managerial and practical implications

Digital competence development programmes should begin with discipline-specific pedagogical problems, require lecturers to produce tangible outputs, conduct small-scale trials, and obtain feedback. Such an approach simultaneously strengthens skills, demonstrates usefulness, and builds confidence.

Higher education institutions should establish controlled environments for experimenting with AI, including access to accounts, repositories of use cases, data-related guidance, peer groups, and clear rules specifying permitted activities, transparency requirements, prohibited data inputs, and responsibility for verifying outputs. This human-centred approach is consistent with UNESCO guidance (Miao & Holmes, 2023).

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Evaluations of teaching innovation should focus on pedagogical problems, learner engagement, feedback quality, equity, and evidence of improvement. Lecturers must retain professional responsibility for defining objectives, protecting data, verifying outputs, and disclosing the extent of AI use when necessary.

3. CONCLUSIONS AND RECOMMENDATIONS

This study proposes a model that explains teaching innovation among university lecturers through digital competence and AI acceptance. Analysis of 386 observations indicates that the measurement scales exhibited adequate reliability. Digital competence positively predicts AI acceptance and teaching innovation, while AI acceptance is the stronger predictor of teaching innovation. AI acceptance plays a partially mediating role, and the model explains 48.7% of the variance in teaching innovation. The findings suggest that technological competence is translated into pedagogical value when lecturers perceive AI as useful and appropriate for their professional tasks.

Theoretically, the study integrates DigCompEdu with TAM and UTAUT, illuminating the mechanism through which digital competence is translated into innovative teaching practices. In practical terms, higher education institutions should develop digital and AI competence through discipline-specific training linked to authentic teaching scenarios. Universities should create controlled AI experimentation environments and provide infrastructure and communities of practice. They should also establish guidelines on data protection, transparency in AI use, output verification, and lecturers' professional responsibilities. Evaluations of innovation should be based on the quality of learning materials, learner engagement, effective feedback, and equity.

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