

THE EFFECT OF DIGITAL COMPETENCY AMONG UNIVERSITY TEACHERS ON PERSONALIZED INSTRUCTION IN SHANDONG PROVINCE OF CHINA WITH THE MEDIATION OF TECHNOLOGICAL SELF-EFFICACY

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Abstract: *This article examines how university teachers' digital competency influences the implementation of personalized instruction in Shandong Province, China, and whether technological self-efficacy mediates this relationship. The study responds to a persistent policy-practice gap in digital higher education: while universities have invested heavily in smart platforms, learning management systems, and digital teaching infrastructure, personalized instruction remains uneven across institutional contexts. Drawing on digital competency frameworks, Bandura's self-efficacy theory, differentiated instruction theory, and the TPACK framework, the study conceptualizes digital competency as a multidimensional teacher capacity that can support responsive, data-informed, and learner-centered instruction. A quantitative cross-sectional survey was conducted among full-time university teachers in Shandong Province. A total of 500 questionnaires were returned, and 428 valid responses were retained after data screening. Data were analyzed using SPSS and AMOS. Confirmatory factor analysis supported a second-order measurement model consisting of Digital Competency, Technological Self-Efficacy, and Personalized Instruction. The final model retained 63 items across 13 first-order dimensions. The structural model showed excellent fit: chi-square = 1898.840, df = 1873, p = .333, chi-square/df = 1.014, CFI = .997, TLI = .997, and RMSEA = .006. Digital competency significantly predicted personalized instruction (beta = .291, p < .001) and technological self-efficacy (beta = .639, p < .001). Technological self-efficacy also significantly predicted personalized instruction (beta = .577, p < .001). Mediation analysis showed that technological self-efficacy partially mediated the relationship between digital competency and personalized instruction, with a standardized indirect effect of .369 and a total effect of .660. The findings suggest that digital competency affects personalized instruction not only as a technical-pedagogical capability but also through teachers' confidence in applying technology. The findings provide empirical evidence regarding how university teachers' digital*

competency and technological self-efficacy jointly shape personalized instruction in Chinese higher education.

Keywords: *Digital competency; technological self-efficacy; personalized instruction; university teachers in Shandong Province; structural equation modelling*

Introduction

The rapid advancement of digital technologies, artificial intelligence (AI), big data, cloud computing, and learning analytics has fundamentally transformed higher education worldwide. Universities are no longer expected merely to transmit disciplinary knowledge; they are increasingly required to cultivate students' digital literacy, critical thinking, creativity, problem-solving abilities, and lifelong learning competencies that are essential in the digital economy (OECD, 2023; UNESCO, 2024; World Economic Forum [WEF], 2025). Consequently, higher education institutions are undergoing a pedagogical transition from teacher-centred instruction toward more flexible, learner-centred, and technology-enhanced teaching approaches that emphasize personalization, interaction, and active student engagement (Bond et al., 2024; OECD, 2023).

Recognizing this global trend, governments around the world have introduced policies to accelerate digital transformation in education. Recent international policy discussions increasingly position teacher digital competency as a fundamental condition for meaningful educational transformation (UNESCO, 2024). Likewise, the OECD (2023) emphasizes that teachers must possess not only technical skills but also the pedagogical capability to integrate digital technologies meaningfully into teaching and learning. The World Economic Forum (2025) further highlights that educators are expected to leverage artificial intelligence and digital technologies to facilitate adaptive learning, personalized feedback, and data-informed instructional decision-making. These international initiatives collectively indicate that digital competency has become a core professional competency for university teachers rather than simply a technological skill.

China has actively aligned its higher education reform agenda with these international developments. In recent years, the Ministry of Education of China has introduced several national policies to promote education digitalization, including the Education Informatization 2.0 Action Plan, China's Education Modernization 2035, and the Teacher Digital Literacy Standard (Ministry of Education of the People's Republic of China, 2018, 2023; State Council of the People's Republic of China, 2019). These policies advocate the deep integration of digital technologies into teaching, learning, assessment, and educational management, while encouraging universities to adopt personalized, intelligent, and student-centred instructional approaches. More recently, artificial intelligence has been identified as a strategic driver for educational innovation, requiring university teachers to continuously improve their digital competency to meet emerging instructional demands.

Among various instructional innovations, personalized instruction has received increasing attention because it enables teachers to accommodate learners' diverse backgrounds, learning preferences, interests, abilities, and developmental needs. Rather than adopting a "one-size-fits-all" teaching model, personalized instruction encourages differentiated learning objectives, adaptive learning pathways, flexible teaching strategies, and continuous formative assessment (Tomlinson & Imbeau, 2010; Bond et al., 2024). Recent empirical studies have demonstrated

that personalized instruction can improve students' learning motivation, engagement, academic achievement, self-regulated learning, and learning satisfaction across different educational contexts (Bi et al., 2024; Coll et al., 2022). Consequently, personalized instruction has become an important pedagogical objective in the digital transformation of higher education.

Although digital technologies provide new opportunities for implementing personalized instruction, effective technology integration ultimately depends on teachers. Existing studies consistently suggest that university teachers' digital competency significantly influences their ability to design digital learning activities, integrate educational technologies, support student interaction, and facilitate individualized learning experiences (Howard et al., 2023; Breznik et al., 2024). However, possessing digital competency alone may not guarantee effective instructional implementation. Teachers' beliefs regarding their capability to use technology, commonly conceptualized as technological self-efficacy, have also been identified as an important determinant of technology-supported teaching behaviour (Bandura, 1997; Scherer et al., 2019). Teachers with stronger technological self-efficacy are generally more willing to experiment with innovative instructional approaches, overcome technological challenges, and sustain technology integration in classroom practice.

Despite the growing body of literature on digital competency, technology integration, and personalized learning, relatively limited empirical evidence has simultaneously examined the relationships among university teachers' digital competency, technological self-efficacy, and personalized instruction within a unified structural model, particularly in the context of Chinese higher education. Most previous studies have focused on primary and secondary school teachers, preservice teachers, or general technology adoption, while comparatively little attention has been paid to university teachers responsible for cultivating digitally competent graduates in increasingly complex higher education environments (Howard et al., 2023; Breznik et al., 2024). Furthermore, provincial contexts such as Shandong, which possesses one of China's largest higher education systems, remain underrepresented in existing empirical research.

To address these research gaps, the present study investigates the influence of university teachers' digital competency on personalized instruction and examines the mediating role of technological self-efficacy among full-time university teachers in Shandong Province, China. Using structural equation modelling (SEM), this study seeks to provide empirical evidence that contributes to the understanding of digital pedagogy in higher education while offering practical implications for teacher professional development and digital education policy.

Research Problem, Objectives, and Hypotheses

The central problem addressed in this study is the gap between digital infrastructure and personalized teaching practice. Many universities have access to digital platforms and online tools, yet the level of personalized instruction implemented in regular teaching remains inconsistent. Digital tools alone do not guarantee student-centered pedagogy. Teachers must be able to select tools appropriately, use data ethically, design differentiated learning pathways, and evaluate learning outcomes. Moreover, they must believe that they are capable of using technology effectively. Without such confidence, digital technologies may simply reproduce traditional lecture-centered practice in electronic form.

The problem is also theoretical. Previous research has often examined digital competency, technology adoption, self-efficacy, and differentiated instruction separately. There is still a need

for an integrated model explaining how digital competency contributes to personalized instruction and how technological self-efficacy functions as a psychological pathway in this process. The present study therefore combines digital competency frameworks, self-efficacy theory, differentiated instruction theory, and the TPACK perspective to explain the relationships among teacher capability, confidence, and instructional practice.

Table 1: Research Objectives, Research Questions, and Hypotheses

Objective/Question /Hypothesis	Focus	Analytical approach
RO1/RQ1	Assess the current level of Digital Competency among university teachers in Shandong Province.	Descriptive statistics
RO2/RQ2	Measure the current level of Personalized Instruction practices.	Descriptive statistics
RO3/RQ3	Evaluate the current level of Technological Self-Efficacy.	Descriptive statistics
RO4/RQ5/H2	Examine the effect of Digital Competency on Technological Self-Efficacy.	SEM direct path
RO5/RQ4/H1	Investigate the effect of Digital Competency on Personalized Instruction.	SEM direct path
RO6/RQ6/H3	Explore the effect of Technological Self-Efficacy on Personalized Instruction.	SEM direct path
RO7/RQ7/H4	Examine the mediating role of Technological Self-Efficacy.	SEM mediation analysis

The main objective of the study was to investigate the effect of digital competency on personalized instruction among university teachers in Shandong Province, China, with technological self-efficacy as a mediating variable. Seven specific objectives guided the study: to assess the current level of digital competency, personalized instruction, and technological self-efficacy; to examine the direct effect of digital competency on personalized instruction; to examine the effect of digital competency on technological self-efficacy; to examine the effect of technological self-efficacy on personalized instruction; and to test the mediating role of technological self-efficacy.

Literature Review and Theoretical Framework

Digital Competency among University Teachers

Within higher education, digital competency has gradually evolved from a technology-oriented capability into a broader professional capacity involving pedagogical decision-making, ethical awareness, and continuous digital development. In educational contexts, digital competency has evolved beyond basic technical skills and increasingly emphasizes the integration of digital technologies with pedagogical practices (Redecker, 2017; Falloon, 2020). For university teachers, digital competency involves not only technological proficiency but also the capability to design technology-supported learning environments, facilitate student engagement, and enhance teaching effectiveness.

Recent studies have further highlighted the importance of digital competency among higher education teachers. The Higher Education Digital Competence (HeDiCom) framework proposed by Howard et al. (2023) emphasized that university teachers' digital competency is a

multidimensional construct involving digital teaching practices, professional development, and responsible technology use. Similarly, Inamorato dos Santos et al. (2023) argued that academics' digital competence should integrate technological, pedagogical, and ethical dimensions to support meaningful digital transformation in higher education. Empirical evidence also suggests that higher levels of teachers' digital competency contribute to improved technology integration and innovative teaching practices (Breznik et al., 2024).

In the context of personalized instruction, digital competency is particularly important because teachers need to utilize digital tools to identify students' learning needs, provide adaptive resources, and implement learner-centred strategies. Therefore, this study considers digital competency as a key antecedent of personalized instruction and examines its relationship with university teachers' instructional practices.

Technological Self-Efficacy

Technological self-efficacy refers to an individual's belief in their capability to effectively use digital technologies to accomplish specific tasks and achieve desired outcomes (Bandura, 1997). In educational settings, it reflects teachers' confidence in integrating digital technologies into instructional planning, classroom implementation, and assessment. In practice, teachers with higher technological self-efficacy are generally more willing to adopt innovative teaching approaches, overcome technological challenges, and persist when encountering difficulties during technology integration.

Recent studies have extended Bandura's self-efficacy theory to digital teaching environments. Backfisch et al. (2021) reported that teachers' technological self-efficacy is a significant predictor of technology acceptance and effective digital teaching practices. Likewise, Howard et al. (2023) found that university teachers with stronger confidence in using educational technologies were more likely to adopt innovative pedagogical strategies and engage in continuous digital professional development. As digital learning environments become increasingly supported by artificial intelligence and learning analytics, technological self-efficacy has become an essential psychological factor influencing teachers' willingness to transform traditional teaching practices into more student-centred and technology-enhanced learning experiences.

In the context of personalized instruction, technological self-efficacy enables teachers to confidently employ digital platforms, adaptive learning technologies, and data-informed instructional strategies to address students' diverse learning needs. Therefore, technological self-efficacy is expected not only to directly support personalized instructional practices but also to strengthen the influence of digital competency on teachers' instructional behaviour. Accordingly, this study proposes that technological self-efficacy functions as an important mediating variable linking digital competency and personalized instruction.

Personalized Instruction and Differentiated Teaching

Personalized instruction refers to a learner-centred teaching approach that adapts instructional objectives, learning activities, teaching strategies, and assessment methods according to students' individual characteristics, interests, abilities, and learning needs (Tomlinson, 2014). Unlike traditional teacher-centred instruction, personalized instruction emphasizes adapting teaching decisions according to students' differences in readiness, learning preferences, and developmental needs.

Recent research has reinforced the importance of personalized instruction in higher education, particularly in digitally enhanced learning environments. Coll et al. (2022) suggested that effective personalized learning requires teachers to continuously monitor students' progress and provide adaptive instructional support based on individual learning needs. Similarly, Bi et al. (2024) found that teachers' attitudes and instructional competencies play a critical role in successfully implementing personalized instruction in university classrooms. With the increasing use of digital technologies and artificial intelligence, personalized instruction has become more feasible through adaptive learning platforms, learning analytics, and timely formative feedback, enabling teachers to make evidence-based instructional decisions (Bond et al., 2024).

Successful implementation of personalized instruction depends not only on the availability of digital technologies but also on teachers' professional competencies and confidence in applying them effectively. University teachers therefore need sufficient digital competency and technological self-efficacy to design differentiated learning activities, provide individualized learning resources, and support students with diverse academic backgrounds. Consequently, personalized instruction is regarded in this study as an important educational outcome influenced by teachers' digital competency and technological self-efficacy.

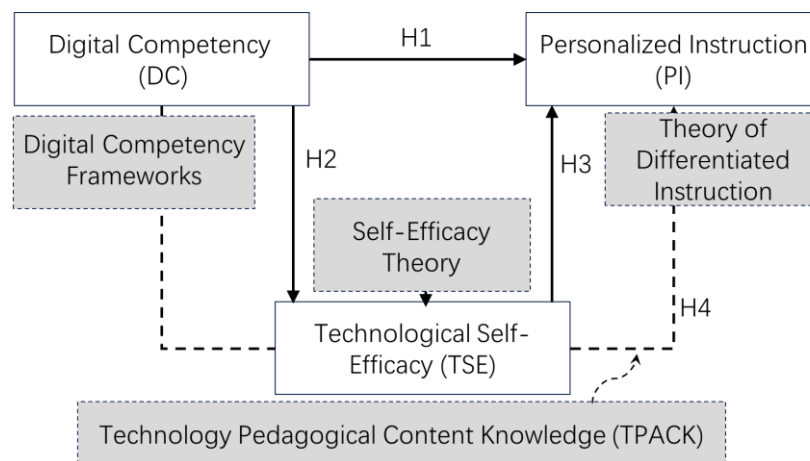


Figure 1: Integrated Theoretical Framework

Hypotheses Development

Previous studies have consistently shown that teachers' digital competency plays a fundamental role in promoting effective technology integration and innovative pedagogical practices. University teachers with stronger digital competency are better able to design learner-centred learning environments, utilize digital resources, and support personalized learning through technology (Howard et al., 2023; Breznik et al., 2024). At the same time, teachers' confidence in using educational technologies, commonly referred to as technological self-efficacy, has been identified as an important psychological factor influencing their willingness to adopt digital innovations and implement technology-enhanced instruction (Bandura, 1997; Scherer et al., 2019). Recent research also suggests that personalized instruction increasingly depends on teachers' ability to integrate digital technologies and adapt teaching strategies to meet students' diverse learning needs (Coll et al., 2022; Bond et al., 2024).

Based on these theoretical perspectives and previous empirical findings, this study assumes that digital competency influences personalized instruction and technological self-efficacy both

directly, and indirectly through teachers' technological self-efficacy. Accordingly, the following hypotheses are proposed:

H1: Digital competency has a positive effect on personalized instruction.

H2: Digital competency has a positive effect on technological self-efficacy.

H3: Technological self-efficacy has a positive effect on personalized instruction.

H4: Technological self-efficacy mediates the relationship between digital competency and personalized instruction.

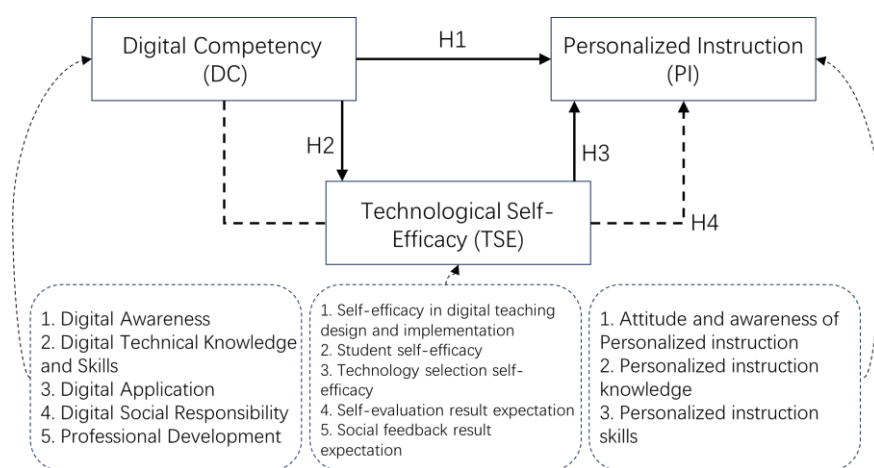


Figure 2: Conceptual Framework and Research Hypotheses

Methodology

Research Design and Participants

A quantitative cross-sectional survey design was employed to examine the relationships among the three latent constructs. This design was appropriate because the research aimed to assess the levels of key constructs and test hypothesized relationships among latent variables using structural equation modeling. The unit of analysis was the individual full-time university teacher. The population consisted of full-time teachers working in universities in Shandong Province, China. The inclusion criteria required respondents to be full-time teaching staff at undergraduate or postgraduate institutions in Shandong, have at least one year of university-level teaching experience, have used digital teaching platforms in instructional activities, and have participated in formal or informal training related to educational technologies or digital pedagogy.

Data were collected through Questionnaire Star. A total of 500 questionnaires were returned. After data screening, 72 questionnaires were removed because they failed eligibility or quality checks. The excluded cases included respondents who failed screening questions, straight-line responses, responses completed in less than five minutes, W-shaped or zigzag response patterns, and responses with abnormal demographic information. The final valid dataset contained 428 responses, producing a valid response rate of 85.6%.

The sample was sufficiently large for confirmatory factor analysis and structural equation modeling. In SEM, sample size requirements depend on model complexity, estimation method, distributional properties, and indicator quality. A sample of 428 cases provided an adequate basis for estimating the second-order measurement and structural models.

Table 2: Data Screening and Valid Response Rate

Screening category	Number	Percentage/decision
Total returned questionnaires	500	100.0%
Failed screening questions	9	Excluded
Straight-line response patterns	31	Excluded
Completion time below five minutes	23	Excluded
W-shaped or zigzag response patterns	4	Excluded
Abnormal demographic information	5	Excluded
Total invalid questionnaires	72	14.4%
Valid questionnaires retained	428	85.6%

Instrument and Measurement

The questionnaire consisted of screening questions, measurement items, and demographic questions. The core constructs were Digital Competency, Technological Self-Efficacy, and Personalized Instruction. All measurement items were rated using a five-point Likert scale ranging from 1 = strongly disagree to 5 = strongly agree. Higher scores indicated higher perceived levels of the corresponding construct.

The questionnaire was adapted from several validated instruments widely used in previous studies. Minor modifications were made to ensure consistency with the context of Chinese higher education and the objectives of the present study.

Digital Competency was measured across five dimensions: Digital Awareness, Digital Technical Knowledge and Skills, Digital Application, Digital Social Responsibility, and Professional Development. Technological Self-Efficacy was measured across five dimensions: Digital Teaching Design and Implementation Self-Efficacy, Student Self-Efficacy, Technology Selection Self-Efficacy, Self-Evaluation Result Expectation, and Social Feedback Result Expectation. Personalized Instruction was measured across three dimensions: Attitude and Awareness of Personalized Instruction, Personalized Instruction Knowledge, and Personalized Instruction Skills.

Table 3: Sources and Adaptation of the Measurement Instruments

Construct	Source	Instrument Status	
Digital Competency	Ministry of Education of China (2022); Howard et al. (2023); Breznik et al. (2024)	Adapted	Adapted
Technological Self-Efficacy	Compeau & Higgins (1995); Holden & Rada (2011)	Adapted	Adapted
Personalized Instruction	Tomlinson (2014); Coubergs et al. (2017); Coll et al. (2022); Bi et al. (2024)	Adapted	Adapted

The measurement structure was treated as multidimensional. The study first assessed the first-order dimensions and then specified Digital Competency, Technological Self-Efficacy, and Personalized Instruction as second-order constructs. This approach was suitable because the

conceptual framework focused on the three main constructs while acknowledging their internal dimensional structure.

Data Analysis

Data analysis was conducted using SPSS and AMOS. SPSS was used for data coding, screening, descriptive statistics, and preliminary assumption testing. AMOS was used for confirmatory factor analysis, structural equation modeling, and mediation analysis. Before the main analyses, the dataset was examined for missing values, normality, outliers, multicollinearity, common method bias, and response quality.

No missing values were identified in the final dataset. Univariate normality was acceptable because the skewness and kurtosis values of the measurement items were within acceptable ranges. Multivariate normality was not fully achieved, which is common in survey-based Likert-scale studies involving many observed variables. Therefore, maximum likelihood estimation was used with caution, and bootstrapping was applied for mediation analysis. No case met the adopted multivariate outlier deletion criterion. Multicollinearity was also not a serious concern because standardized regression weights and inter-construct correlations were below problematic thresholds. Common method bias was examined through Harman's single-factor test and full collinearity VIF, and the results indicated that common method bias was not a serious threat.

For the measurement model, standardized factor loadings, composite reliability, average variance extracted, discriminant validity, and model fit were assessed. For the structural model, model fit, path coefficients, critical ratios, p-values, R-squared values, and direct, indirect, and total effects were examined. Mediation was interpreted by comparing direct and indirect effects and by considering whether the mediator transmitted a meaningful portion of the total effect.

Findings and Analysis

Demographic Profile

The demographic profile indicated that the sample represented a broad range of university teachers in Shandong Province. The gender distribution was relatively balanced: 46.3% of respondents were male, 51.9% were female, and 1.9% preferred not to say. The largest age group was 36 to 45 years old (37.6%), followed by 46 to 55 years old (30.6%), below 35 years old (25.9%), and 56 years and above (5.8%). The sample included different academic ranks, with assistant lecturers or lecturers accounting for 24.8%, senior lecturers 23.6%, assistant professors 19.9%, associate professors 22.7%, and professors 9.1%.

Teaching experience was also diverse. Respondents with 6 to 10 years of teaching experience formed the largest group (30.1%), followed by those with 11 to 20 years (26.2%). Most respondents worked in provincial public universities, and the sample covered doctoral degree-granting, master's degree-granting, and other undergraduate universities. The disciplinary background of teachers was also broad, with education and teacher training, engineering and technology, humanities and social sciences, natural sciences, and economics, management, and business being among the larger categories. All respondents reported participation in digital teaching training, and 78.8% reported using digital tools either daily or weekly.

Descriptive Statistics of Main Constructs

The descriptive statistics showed that the three main constructs all recorded mean scores above the neutral midpoint of the five-point Likert scale. Digital Competency had a mean of 3.587 and a standard deviation of 0.579. Technological Self-Efficacy had a mean of 3.640 and a standard deviation of 0.558. Personalized Instruction recorded the highest mean, with a mean of 3.703 and a standard deviation of 0.584. These results suggest that respondents generally perceived themselves as having moderately high digital competency, technological self-efficacy, and personalized instruction practices.

At the dimension level, all dimensions also recorded mean scores above 3.00. For Digital Competency, Digital Technical Knowledge and Skills and Digital Social Responsibility recorded relatively high means. For Technological Self-Efficacy, Student Self-Efficacy and Technology Selection Self-Efficacy were among the higher dimensions. For Personalized Instruction, Personalized Instruction Knowledge recorded the highest mean, followed by Personalized Instruction Skills. The skewness and kurtosis values of the constructs and dimensions indicated no serious departure from univariate normality.

Table 4: Descriptive Statistics of the Main Constructs

Construct	Items	Mean	SD	Minimum	Maximum	Skewness	Kurtosis
Digital Competency	26	3.587	0.579	2.115	4.808	-0.241	-0.511
Technological Self-Efficacy	19	3.640	0.558	2.000	4.895	-0.265	-0.423
Personalized Instruction	25	3.703	0.584	1.880	4.920	-0.364	-0.271

Table 5: Descriptive Statistics of Construct Dimensions

Construct	Dimension	Items	Mean	SD	Skewness	Kurtosis
DC	Digital Awareness	4	3.557	0.783	-0.310	-0.472
DC	Digital Technical Knowledge and Skills	5	3.618	0.754	-0.268	-0.586
DC	Digital Application	7	3.568	0.758	-0.392	-0.271
DC	Digital Social Responsibility	5	3.614	0.750	-0.288	-0.558
DC	Professional Development	5	3.579	0.704	-0.227	-0.501
TSE	Digital teaching design and implementation	4	3.597	0.742	-0.422	-0.264
TSE	Student self-efficacy	4	3.675	0.754	-0.244	-0.562
TSE	Technology selection self-efficacy	4	3.652	0.739	-0.360	-0.291
TSE	Self-evaluation result expectation	4	3.649	0.765	-0.315	-0.356
TSE	Social feedback result expectation	3	3.621	0.801	-0.499	-0.071
PI	Attitude and awareness	6	3.646	0.764	-0.422	-0.201
PI	Personalized instruction knowledge	6	3.739	0.709	-0.502	-0.074
PI	Personalized instruction skills	13	3.714	0.670	-0.388	-0.443

Measurement Model Assessment

Confirmatory factor analysis was conducted to evaluate the measurement model. The initial model contained 70 items across 13 first-order dimensions. The item assessment showed that all standardized factor loadings exceeded the minimum threshold of .50. However, seven items had relatively weaker loadings or contributed less strongly to construct validity. Based on the combined criteria of standardized loading, composite reliability, theoretical coverage, and second-order model logic, seven items were removed: DC_PD4, TSE_DTD2, TSE_SEL2, PI_SK1, PI_SK2, PI_SK6, and PI_SK11. The final measurement model retained 63 items across 13 first-order dimensions.

The measurement model was treated as a second-order model. Digital Competency was represented by five first-order dimensions, Technological Self-Efficacy by five first-order dimensions, and Personalized Instruction by three first-order dimensions. This model reflected the theoretical structure of the study more accurately than a flat model because the research hypotheses concerned the relationships among the three broad constructs rather than the separate effects of all 13 dimensions.

Model fit was assessed using chi-square/df, CFI, TLI, and RMSEA. The measurement model demonstrated acceptable to excellent fit. One theoretically justified error covariance was added between TSE_DTD1 and DC_APP4 during model refinement because both items referred to the use of appropriate technology for instructional purposes. The modification was made cautiously and was not based solely on statistical improvement.

Table 6: Measurement Model Fit Before and After Model Refinement

Fit index	Before refinement	After refinement	Criterion	Decision
chi-square	1863.608	1845.708	Smaller preferred	Improved
df	1812	1811	—	—
p-value	0.195	0.280	$p > 0.05$ preferred	Achieved
chi-square/df	1.028	1.019	≤ 3.00	Achieved
CFI	0.995	0.997	≥ 0.90	Achieved
TLI	0.995	0.996	≥ 0.90	Achieved
RMSEA	0.008	0.007	≤ 0.08	Achieved

Table 7: Construct Reliability and Convergent Validity after Item Refinement

Construct	Items retained	CR	AVE	MaxR (H)	Interpretation
DC_DA	4	0.792	0.489	0.801	Reliable; AVE close to 0.50
DC_DTK	5	0.823	0.483	0.826	Reliable; AVE close to 0.50
DC_APP	7	0.872	0.494	0.877	Reliable; AVE close to 0.50
DC_DSR	5	0.815	0.469	0.817	Reliable; AVE slightly below 0.50
DC_PD	4	0.740	0.419	0.758	Reliable; AVE below 0.50
TSE_DTD	3	0.708	0.448	0.714	Reliable; AVE below 0.50
TSE_STU	4	0.784	0.478	0.793	Reliable; AVE close to 0.50
TSE_SEL	3	0.704	0.444	0.714	Reliable; AVE below 0.50
TSE_SER	4	0.767	0.452	0.772	Reliable; AVE below 0.50
TSE_SFR	3	0.741	0.488	0.743	Reliable; AVE close to 0.50
PI_AA	6	0.866	0.519	0.868	Reliable; AVE acceptable
PI_KN	6	0.813	0.422	0.824	Reliable; AVE below 0.50
PI_SK	9	0.896	0.492	0.902	Reliable; AVE close to 0.50

Structural Model Assessment

After the measurement model had been assessed, the structural model was tested. The model included three paths: Digital Competency to Personalized Instruction, Digital Competency to Technological Self-Efficacy, and Technological Self-Efficacy to Personalized Instruction. Digital Competency was treated as the exogenous construct, while Technological Self-Efficacy and Personalized Instruction were endogenous constructs.

The structural model demonstrated excellent fit. The chi-square value was 1898.840 with 1873 degrees of freedom and a non-significant p-value of .333. The normed chi-square value was 1.014, which was below the recommended threshold of 3.00. CFI and TLI were both .997, exceeding the recommended criterion of .90 and indicating very strong incremental fit. RMSEA was .006, far below the threshold of .08 and indicating excellent approximation fit. These indices showed that the structural model was consistent with the observed data.

Table 8: Structural Model Fit Indices

Fit index	Result	Recommended criterion	Decision
chi-square	1898.840	Smaller value preferred	Acceptable
df	1873	—	—
p-value	.333	$p > .05$ preferred	Achieved
chi-square/df	1.014	≤ 3.00	Achieved
CFI	.997	$\geq .90$	Achieved
TLI	.997	$\geq .90$	Achieved
RMSEA	.006	$\leq .08$	Achieved

Table 9: Summary of Direct Structural Effects

Hypothesis	Path	Unstandardized estimate	S.E.	C.R.	p-value	Standardized beta	Decision
H1	DC → PI	0.298	0.078	3.837	< 0.001	0.291	Supported
H2	DC → TSE	0.659	0.091	7.219	< 0.001	0.639	Supported
H3	TSE → PI	0.573	0.094	6.064	< 0.001	0.577	Supported

All three direct structural paths were significant and positive. Digital Competency had a significant positive effect on Personalized Instruction, supporting H1. Digital Competency had a significant positive effect on Technological Self-Efficacy, supporting H2. Technological Self-Efficacy had a significant positive effect on Personalized Instruction, supporting H3. The strongest direct effect was from Digital Competency to Technological Self-Efficacy, followed by Technological Self-Efficacy to Personalized Instruction. The direct effect of Digital Competency on Personalized Instruction remained significant even after Technological Self-Efficacy was included in the model.

Table 10: Squared Multiple Correlations

Endogenous construct	Predictor(s)	R-squared	Variance explained
Technological Self-Efficacy	Digital Competency	0.409	40.9%
Personalized Instruction	Digital Competency and Technological Self-Efficacy	0.632	63.2%

Mediation Analysis

The mediation analysis examined whether Technological Self-Efficacy mediated the relationship between Digital Competency and Personalized Instruction. The standardized direct effect of Digital Competency on Personalized Instruction was .291. The standardized indirect effect through Technological Self-Efficacy was .369. The standardized total effect was .660. The indirect effect was larger than the direct effect, suggesting that a substantial portion of the influence of Digital Competency on Personalized Instruction operated through teachers' confidence in using technology.

The proportion mediated was calculated by dividing the indirect effect by the total effect. The result was $.369 / .660 = .559$, indicating that approximately 55.9% of the total effect of Digital Competency on Personalized Instruction was transmitted through Technological Self-Efficacy. Because the direct path from Digital Competency to Personalized Instruction remained significant while the indirect effect was also meaningful, the mediation type was interpreted as partial mediation. Thus, H4 was supported.

This result is theoretically important. It indicates that digital competency contributes to personalized instruction in two ways. First, it has a direct pedagogical effect: teachers with stronger digital competency are better prepared to use digital tools and resources to support individualized learning. Second, it has an indirect psychological effect: digital competency strengthens teachers' technological self-efficacy, which then increases the likelihood that teachers will implement personalized instruction.

Table 11: Mediation Effects of Technological Self-Efficacy

Relationship	Direct effect	Indirect effect	Total effect	Proportion mediated	Mediation type
DC -> TSE -> PI	0.291	0.369	0.660	55.9%	Partial mediation

Table 12: Summary of Research Questions and Hypothesis Testing

Research question/ hypothesis	Statistical evidence	Finding/decision
RQ1	DC: M = 3.587, SD = 0.579	Moderately high Digital Competency
RQ2	PI: M = 3.703, SD = 0.584	Moderately high Personalized Instruction
RQ3	TSE: M = 3.640, SD = 0.558	Moderately high Technological Self-Efficacy
H1/RQ4	beta = 0.291, p < .001	DC significantly predicted PI; supported
H2/RQ5	beta = 0.639, p < .001	DC significantly predicted TSE; supported
H3/RQ6	beta = 0.577, p < .001	TSE significantly predicted PI; supported
H4/RQ7	Indirect effect = 0.369; total effect = 0.660	TSE partially mediated DC -> PI; supported

Discussion

Digital Competency as a Foundation for Personalized Instruction

The findings provide empirical support for the argument that digital competency is an important foundation for personalized instruction among university teachers. The significant direct effect of Digital Competency on Personalized Instruction indicates that teachers who have stronger digital awareness, technical skills, application capability, digital responsibility, and professional development orientation are more likely to implement personalized teaching practices. This result aligns with the view that digital competency is not limited to operational knowledge but includes the capacity to integrate digital tools into pedagogical design and student support.

The direct effect of Digital Competency on Personalized Instruction was positive but smaller than the indirect effect through Technological Self-Efficacy. This pattern suggests that digital competency matters, but its influence is not entirely automatic. Teachers may possess technical knowledge and digital resources, yet personalized instruction requires confidence, decision-making, and willingness to adapt. The finding therefore extends digital competency research by showing that the pedagogical value of digital competency is partly dependent on teachers' self-beliefs.

In the Shandong higher education context, this finding is practically meaningful. Universities may have digital platforms and infrastructure, but the effective use of these resources depends on teachers' ability to connect technology with instructional objectives. Digital competency can help teachers use learning platforms to collect student feedback, adopt online quizzes to diagnose learning gaps, provide differentiated materials, and support student learning through flexible communication channels. Such practices are essential for personalized instruction in large and diverse university classrooms.

Digital Competency as a Predictor of Technological Self-Efficacy

The strongest direct path in the structural model was from Digital Competency to Technological Self-Efficacy. This result is consistent with self-efficacy theory because teachers with more digital knowledge and application experience are likely to develop stronger beliefs in their ability to use technology. Mastery experiences are a powerful source of self-efficacy. When teachers successfully use digital tools in teaching, they gain confidence that they can perform similar tasks in the future. Therefore, digital competency can be understood as both a skill base and an experiential source of technological self-efficacy.

This result also has implications for professional development. Training programs that focus only on technical demonstrations may not be sufficient. Teachers need opportunities to practice, apply, receive feedback, and see successful outcomes. Such experiences can strengthen self-efficacy more effectively than passive training. Universities should therefore design professional development programs that combine technical training, pedagogical design, peer observation, guided practice, and reflective feedback. When digital competency training is linked to authentic teaching tasks, it is more likely to increase technological self-efficacy.

The finding further suggests that teacher confidence in technology use is not merely a personality trait. It can be developed through structured learning opportunities, institutional support, and successful practice. This is important for universities where faculty members may differ in age, discipline, teaching experience, and prior exposure to digital teaching. A strong digital competency development system can reduce confidence gaps and support more consistent personalized instruction across institutions.

Technological Self-Efficacy as a Driver of Personalized Instruction

Technological Self-Efficacy had a strong positive effect on Personalized Instruction. This indicates that teachers who are more confident in using technology are more likely to implement personalized teaching practices. Personalized instruction often involves complexity and uncertainty. Teachers may need to select suitable digital tools, interpret learner data, adjust content, provide targeted feedback, and manage learning differences. Confidence in using technology helps teachers approach these tasks with greater persistence and willingness to experiment.

This finding supports the theoretical argument that self-efficacy connects capability with action. Teachers with lower technological self-efficacy may use digital tools in limited ways, such as uploading slides or conducting standard online lectures. Teachers with higher technological self-efficacy may be more willing to use platforms interactively, create differentiated learning pathways, and monitor student progress through digital feedback systems. Therefore, technological self-efficacy is not simply a psychological outcome; it is also a predictor of pedagogical innovation.

The result also highlights the importance of emotional and cognitive readiness in digital transformation. University teachers may face workload pressure, uncertainty about new platforms, or anxiety about technical failure. Professional development should therefore address not only competence but also confidence. Peer support, technical assistance, mentoring, and recognition of successful technology integration can help teachers develop stronger self-efficacy and apply personalized teaching strategies more consistently.

The Mediating Role of Technological Self-Efficacy

The mediation result is one of the central contributions of the study. Technological Self-Efficacy partially mediated the relationship between Digital Competency and Personalized Instruction. The indirect effect accounted for approximately 55.9% of the total effect, indicating that more than half of the influence of Digital Competency on Personalized Instruction was transmitted through teachers' confidence in technology use. This suggests that digital competency becomes more pedagogically powerful when teachers believe they can apply technology successfully.

Partial mediation means that Digital Competency still had a significant direct effect on Personalized Instruction after Technological Self-Efficacy was included in the model. This is theoretically reasonable. Some aspects of digital competency, such as knowing how to use learning platforms, understanding digital ethics, or applying digital resources, may directly support personalized instruction. At the same time, much of the effect is psychological because teachers must feel capable of transforming these competencies into classroom decisions. The dual pathway provides a more nuanced understanding of teacher digital transformation.

The mediation result also helps explain why some institutions with good digital infrastructure may still struggle to implement personalized instruction. Infrastructure and skills are necessary but insufficient. Teachers must also develop confidence that they can use technology effectively for teaching. Institutional strategies should therefore integrate competency development with self-efficacy enhancement. This could include sustained mentoring, instructional design consultation, small-scale experimentation, peer modeling, and feedback on successful practices.

Contributions and Implications

Theoretical Contributions

This study makes several theoretical contributions to the literature on digital competency, technological self-efficacy, and personalized instruction in higher education. First, it provides empirical support for an integrated theoretical model that connects Digital Competency Frameworks, Self-Efficacy Theory, Differentiated Instruction Theory, and the TPACK framework. Rather than treating digital competency as a purely technical concept, the study demonstrates that teachers' digital competency becomes pedagogically meaningful when it is connected to their confidence in using technology and their ability to design learner-centred instruction.

Second, the study extends the application of Self-Efficacy Theory in the context of digital higher education. The findings show that technological self-efficacy is not only an outcome of digital competency but also an important psychological mechanism that links digital competency to personalized instruction. This supports Bandura's (1997) argument that perceived capability influences whether individuals translate knowledge and skills into actual behaviour. In this study, university teachers with stronger digital competency were more likely to develop higher technological self-efficacy, which in turn enhanced their personalized instruction practices.

Third, the study contributes to the literature on personalized instruction by confirming that personalized instruction in higher education depends not only on pedagogical awareness but also on teachers' digital readiness and technological confidence. Personalized instruction requires teachers to identify learner differences, adjust teaching strategies, provide flexible learning support, and use feedback for instructional improvement. These practices are difficult to sustain without adequate digital competency and confidence in technology-supported teaching.

Methodological Contributions

This study also provides methodological contributions by applying structural equation modelling to examine direct and indirect relationships among multidimensional constructs. Digital competency, technological self-efficacy, and personalized instruction were treated as second-order constructs, which allowed the study to preserve their theoretical complexity while testing a clear structural model.

The use of SEM enabled the study to test not only whether digital competency influenced personalized instruction but also how this influence occurred through technological self-efficacy. The results showed that digital competency had a significant direct effect on personalized instruction, a significant effect on technological self-efficacy, and an indirect effect on personalized instruction through technological self-efficacy. This approach provides stronger evidence than simple correlation or regression analysis because it allows simultaneous testing of measurement quality, direct effects, indirect effects, and explained variance.

In addition, the study offers a validated empirical model that may be adapted in future research on teacher digital transformation, technology-supported instruction, and personalized learning. The second-order structure is useful for future studies because it recognizes that digital competency and personalized instruction are not single-dimensional behaviours but broad constructs made up of several interrelated dimensions.

Practical Implications for University Teachers

The findings have direct implications for university teachers. First, teachers should recognize that digital competency involves more than operating digital tools. It includes digital awareness, technical knowledge and skills, digital application, digital social responsibility, and continuous professional development. Therefore, teachers should not only learn how to use platforms or software but also learn how to use digital tools to support diagnosis, differentiation, feedback, and student-centred learning.

Second, teachers should actively develop technological self-efficacy through repeated practice and reflection. Confidence in technology use grows when teachers experience successful digital teaching, receive constructive feedback, and observe effective practices from colleagues. Therefore, teachers can improve their technological self-efficacy by starting with manageable digital teaching tasks, such as using online quizzes for formative assessment, collecting student feedback through digital platforms, or using learning data to adjust classroom activities.

Third, teachers should connect digital tools with personalized instruction. For example, learning management systems can be used to distribute different learning resources to different groups of students; online surveys can be used to identify students' learning needs; digital feedback tools can help monitor learning progress; and adaptive platforms can support flexible learning pathways. These practices can help teachers move from general technology use to meaningful personalized instruction.

Practical Implications for Universities

Universities should design professional development programmes that go beyond basic technical training. Many training programmes focus mainly on how to operate digital platforms, but the findings of this study suggest that technical training alone is not enough. Universities should provide training on how to integrate digital tools into teaching design, assessment, student feedback, learning analytics, and differentiated instruction.

A more effective training model should include hands-on workshops, peer mentoring, classroom-based demonstrations, teaching innovation communities, and follow-up support. Teachers need opportunities to practise digital teaching in authentic teaching contexts rather than only attending one-time lectures or tool demonstrations. Universities should also encourage experienced teachers to share successful cases of technology-supported personalized instruction.

Universities should also provide institutional support for personalized instruction. Personalized teaching requires time, resources, learning data, technical assistance, and flexible teaching arrangements. Therefore, universities should provide reliable digital platforms, technical support teams, instructional design support, and access to learning analytics tools. They should also recognize teachers' efforts in personalized instruction through teaching awards, workload recognition, promotion criteria, or professional development credits.

In addition, universities should pay special attention to teachers with lower technological self-efficacy. These teachers may have digital tools available but may hesitate to use them deeply. Targeted mentoring, peer support, and low-pressure practice opportunities can help reduce anxiety and increase confidence.

Policy Implications

At the policy level, the findings suggest that digital education reform should focus not only on infrastructure but also on teacher capacity and confidence. In many contexts, digital transformation policies emphasize platforms, smart classrooms, online resources, and artificial intelligence tools. However, the results of this study show that infrastructure alone cannot guarantee personalized instruction. Teachers must possess both digital competency and technological self-efficacy to transform digital resources into effective teaching practices.

For Shandong Province, where higher education institutions differ in location, resources, institutional type, and development level, policy support should be more targeted. Provincial education authorities could develop differentiated professional development programmes for different types of universities. For example, universities with weaker digital teaching capacity may need more foundational training and technical support, while more advanced universities may need training in learning analytics, adaptive learning, and AI-supported personalized instruction.

Policy makers should also establish regional collaboration mechanisms. Stronger universities can share digital teaching resources, training modules, and successful personalized instruction cases with less-resourced institutions. Provincial-level digital teaching resource centres, expert networks, and inter-university communities of practice could help reduce institutional disparities and promote more balanced digital transformation.

In addition, teacher digital competency standards should include not only technical skills but also pedagogical application, ethical awareness, digital assessment, data-informed decision-making, and confidence in technology-supported teaching. This would help align teacher development standards with the actual requirements of personalized instruction.

Limitations and Future Research

The findings provide several directions for future research. First, future studies could examine whether the relationships among digital competency, technological self-efficacy, and personalized instruction differ across institution types, disciplines, age groups, or teaching experience levels. Such analysis would provide a more detailed understanding of which groups of teachers need specific forms of support.

Second, future research could use longitudinal designs to examine how teachers' digital competency and technological self-efficacy develop over time. Since confidence and teaching practices may change after training, policy implementation, or teaching innovation projects, longitudinal data would provide stronger evidence of causal development.

Third, future studies could combine quantitative SEM with qualitative interviews or classroom observations. This would help explain how teachers actually use digital tools to personalize instruction in real teaching situations. Such mixed-methods research could provide richer evidence for improving teacher training and institutional support.

Overall, this study suggests that improving personalized instruction in higher education requires a coordinated effort among teachers, universities, and policy makers. Digital competency provides the foundation, technological self-efficacy activates teachers' willingness and confidence, and institutional support enables sustained personalized instruction. Therefore, the

development of personalized instruction should be understood as both a teacher-level and system-level process.

Conclusion

This article examined the effect of digital competency on personalized instruction among university teachers in Shandong Province, China, with technological self-efficacy as a mediating variable. The study was grounded in digital competency frameworks, self-efficacy theory, differentiated instruction theory, and TPACK. Using data from 428 valid respondents and structural equation modeling, the study found that Digital Competency, Technological Self-Efficacy, and Personalized Instruction were positively and significantly related.

Descriptive analysis indicated moderately high levels of digital competency, technological self-efficacy, and personalized instruction among participating university teachers. The measurement model supported a second-order structure with three main constructs and 13 first-order dimensions. The structural model demonstrated excellent fit and supported all direct hypotheses. Digital Competency had a significant positive effect on Personalized Instruction and Technological Self-Efficacy. Technological Self-Efficacy also had a significant positive effect on Personalized Instruction. The model explained 40.9% of the variance in Technological Self-Efficacy and 63.2% of the variance in Personalized Instruction.

The mediation analysis showed that Technological Self-Efficacy partially mediated the relationship between Digital Competency and Personalized Instruction. This finding indicates that digital competency contributes to personalized instruction both directly and indirectly through teachers' confidence in using technology. The indirect pathway was substantial, accounting for 55.9% of the total effect. Therefore, improving personalized instruction in higher education requires more than providing digital tools or training teachers in basic technical skills. Universities must also cultivate teachers' confidence in applying technology for pedagogical purposes.

Taken together, the findings demonstrate that personalized instruction in higher education is shaped not only by teachers' digital capabilities but also by their confidence in applying technology effectively. It suggests that teacher digital transformation is both a competency issue and a self-efficacy issue. For policymakers and university leaders, the findings highlight the need for professional development programs that combine digital skill building, pedagogical application, psychological support, and institutional infrastructure. Such efforts can help university teachers translate digital competence into personalized, responsive, and student-centered instruction.

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