A Study on the Value-Added Evaluation of Digital Competence of University Teachers Based on AHP and Regression Models in the Context of Digital Education

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Abstract: In response to the challenges of evaluating the digital competence of university teachers in the context of educational digital transformation, this study aims to construct a value-added evaluation system and model and propose improvement strategies. Based on the “Teacher Digital Literacy” standards and combined with the characteristics of university teacher development, the evaluation indicator system is refined using the Delphi method to cover multiple dimensions such as digital technology application. The Analytic Hierarchy Process (AHP) is employed to determine indicator weights to ensure data scientificity. Using a hierarchical linear model, we incorporate university classification attributes and regional location into the analysis to construct a dynamic value-added evaluation model, examining the relationship between institutional resources and the development of teachers' digital competencies. While a hierarchical linear model did not reveal statistically significant impacts of individual attributes such as gender and academic title on digital competence value-added, a multiple linear regression model was employed to explore potential associations, showing observed positive relationships with factors like academic title and research output. Based on this, a systematic improvement strategy and educational digital empowerment measures are proposed, comprising “one ecosystem, two main threads, three engines, and four supports,” to assist universities in cultivating innovative talent for the digital age and provide theoretical and practical solutions for the digital transformation of higher education.

1. Introduction

The global digital transformation of education is accelerating, with technologies such as artificial intelligence driving changes in the educational ecosystem. Internationally, the European Union has released relevant action plans that serve as policy models, while domestically, a series of policies have also been introduced, ranging from establishing an intelligent education system to explicitly stating the goal of forging new paths through educational digitalization and emphasizing the digital capabilities of teachers. The digital transformation of higher education is crucial for building a strong education nation. As university faculty members stand at the intersection of education, science and technology, and talent, their digital competence determines the quality of talent cultivation and the effectiveness of the transformation. However, the current evaluation system suffers from issues such as static assessment that overlooks dynamic development, indicators that are out of sync with new demands, and a lack of attention to emerging capabilities. In response, the "Overall Plan for Deepening the Reform of Education Evaluation in the New Era" released in 2020 proposed "exploring value-added evaluation." Therefore, this study aims to explore the value-added evaluation mechanism for university faculty members' digital competence, construct a scientific evaluation system and

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model, and propose improvement strategies, thereby providing a theoretical foundation for the professional development of university faculty and the digital transformation of higher education.

In the wave of educational digital transformation, digital competency assessment has become a focal point in the field of education, with related research being conducted at multiple levels. [1] Khurana M P et al. used a scoping review and the Delphi method to explore digital health competency in medical school education, providing a reference for the cultivation and assessment of digital competencies in the medical field. In the field of vocational education, [2] FEI Z and Kiong T P focused on the application and empowerment of the analytic hierarchy process in the digital competency assessment system for vocational school teachers. [3] Lin H used this method to construct a digital competency evaluation system for teachers at local vocational colleges and demonstrated its application effectiveness; in general higher education, [4] Cabezas-González M et al. focused on theoretical model research to explain students' digital competency levels, and [5] Cabero-Almenara J et al. conducted related research on digital competency among disabled university students. While existing research has made progress, covering different educational stages and populations and employing diverse methods, it primarily focuses on specific groups or single methods, lacking systematic integration and comparative studies of digital competency evaluation systems across different educational contexts. Additionally, there is a gap in comprehensive evaluation models that consider the influence of multidimensional factors. Future research could expand perspectives and strengthen comprehensive studies to develop evaluation systems with greater universality and precision.

2. Model building and solving

2.1 Construction of an evaluation index system and determination of weights based on the Delphi method

In order to construct an evaluation index system for the digital competence of university teachers, first, the names and hierarchical information of the required indicators were sorted and extracted from existing data. Next, questionnaires were distributed to experts to collect their pairwise comparison opinions on the importance of the indicators. Finally, these expert opinions were used to construct a judgment matrix, and the analytic hierarchy process (AHP) was used to determine the weights of each indicator and perform consistency testing.

The Delphi method is a prediction and decision-making method based on expert opinion. Its core idea is to reduce herd mentality and subjective bias in decision-making results by conducting multiple surveys and analyses to reach consensus among experts. Suppose that n experts have scored a certain indicator, and these scores are as follows:

(1) Calculate the average value $\bar{x}$. The average value represents the central tendency or average opinion of the expert group on this indicator.

$$\bar{x} = \frac{1}{n}\sum_{i-1}^{n} x_i \tag{1}$$

(2) Calculate the standard deviation σ. The standard deviation measures the degree of dispersion of expert scores relative to the average value. A larger standard deviation indicates that expert opinions are more dispersed, while a smaller standard deviation indicates that expert opinions are more concentrated.

$$\sigma = \sqrt{\frac{1}{n-1}\sum_{i-1}^{n}(x_i - \bar{x})^2} \tag{2}$$

(3) Calculate the coefficient of variation (CV). The coefficient of variation is the ratio of the standard deviation to the mean. It is a relative measure of dispersion that eliminates the influence of units of measurement, allowing data with different units or different mean levels to be compared. The smaller the CV value, the smaller the relative dispersion of expert opinions, meaning that expert

opinions are more consistent.

$$\mathrm{cv} = \frac{\sigma}{\overline{x}} \tag{3}$$

(4) Judging convergence criteria: If CV < 0.25 or expert opinions tend to be consistent, convergence can be considered to have been achieved.

The Analytic Hierarchy Process (AHP) is a decision-making method that breaks down elements related to decision-making into layers such as objectives, criteria, and plans. Based on this, it conducts qualitative and quantitative analyses of complex and ambiguous issues, particularly suitable for problems that are difficult to fully quantify.

Experts scored on a scale of 1 to 9 to construct a matrix of relative importance for any two indicators $A = [a_{ij}]$:

$$A = \begin{bmatrix} 1 & a_{12} & L & a_{1n} \\ \frac{1}{a_{12}} & 1 & L & a_{2n} \\ M & M & O & M \\ \frac{1}{a_{1n}} & \frac{1}{a_{2n}} & L & 1 \end{bmatrix} \tag{4}$$

The main process of the eigenvector method is as follows: (1) Find the maximum eigenvalue λ_{max} and corresponding eigenvector ω of matrix A; (2) Normalization: $\omega_i = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i}$

Use the consistency index CI and consistency ratio CR to determine whether the expert scores are logically consistent. The calculation formulas are as follows:

$$CI = \frac{\lambda_{\max} - n}{n-1} \tag{5}$$

Regarding the construction and weight determination of the value-added evaluation indicator system for digital competence of university teachers, based on the “Teacher Digital Literacy” framework, the Delphi method was used to preliminarily screen and refine 13 secondary indicators, as shown in Table 1. Subsequently, the Analytic Hierarchy Process (AHP) was employed to calculate the weights of these indicators, followed by rigorous consistency testing.

Table 1 13 detailed secondary indicators

First-level dimension	Secondary dimension	Code
Digital awareness	Digital cognition	B01
Digital awareness	Digital willingness	B02
Digital awareness	Digital will	B03
Digital applications	Digital instructional design	B04
Digital applications	Digital teaching facilities	B05
Digital applications	Digital learning evaluation	B06
Digital applications	Digital collaborative education	B07
Digital social responsibility	Rule of law and ethics	B08
Digital social responsibility	Digital security protection	B09
Digital technology knowledge and skills	Knowledge of digital technologies	B10
Digital technology knowledge and skills	Digital technology skills	B11
Professional development	Digital learning and training	B12
Professional development	Digital teaching innovation	B13

After constructing a pairwise comparison matrix through expert scoring, the calculation results are shown in Table 2, which calculates the AHP weights for each secondary indicator. The consistency index (CI) is 0.0349, and the consistency ratio (CR) is 0.0224. Since the CR value is far less than 0.1, this indicates that the experts' judgments exhibit high consistency, and the judgment matrix is reasonable and acceptable, thereby ensuring the scientific validity and reliability of the calculated weights.

Table 2 AHP weight calculation results

	Indicator code	Name of the secondary indicator	AHP weight
0	MTR01	Digital awareness	0.225202
1	MTR02	Digital willingness	0.096553
2	MTR03	Digital will	0.135623
3	MTR04	Knowledge of digital technologies	0.059987
4	MTR05	Digital technology skills	0.036740
5	MTR06	Digital instructional design	0.023521
6	MTR07	Digital teaching implementation	0.016612
7	MTR08	Digital Chemistry Industry Evaluation	0.036740
8	MTR09	Digital collaboration for the blind	0.023521
9	MTR10	Rule of law and ethics	0.059987
10	MTR11	Digital security protection	0.036740
11	MTR12	Digital learning and training	0.059987
12	MTR13	Digital Teaching Research and Innovation	0.188787

The distribution of AHP indicator weights is shown in Figure 1. The analysis results indicate that in the constructed evaluation system for university teachers' digital competence, indicators such as “digital awareness,” “digital teaching research and innovation,” and “digital will” have significantly higher weights than other items, highlighting the experts' high emphasis on teachers' cognitive abilities, innovative intentions, and proactive initiative, thereby laying a quantitative foundation for subsequent value-added evaluation models.

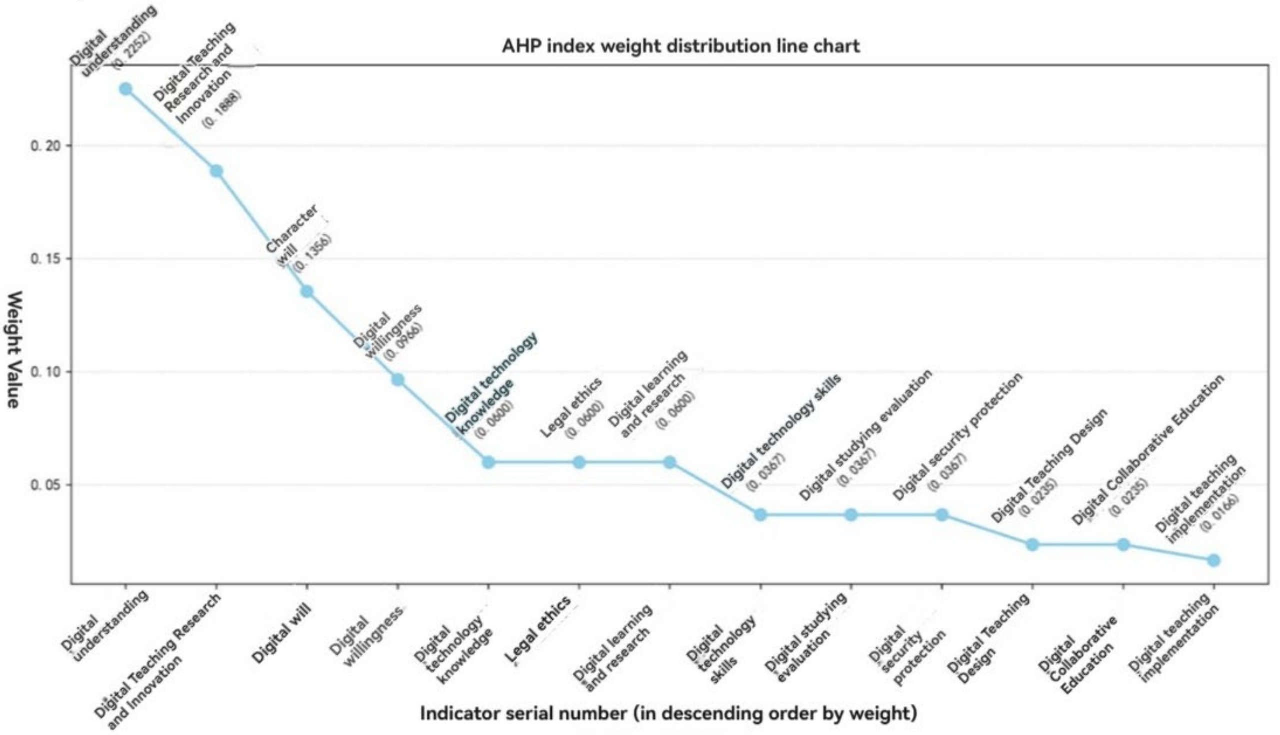

Figure 1 AHP indicator weight distribution line chart

2.2 Construction of a hierarchical linear model and analysis of influencing factors

Given the hierarchical nested structure resulting from teachers' affiliation with schools, a hierarchical linear model was selected. This model can simultaneously handle fixed effects (variables that have a consistent effect on all observation units, such as individual attributes like gender, age, and professional title, as well as university classification attributes and regional location) and random effects (effects that only occur within subgroups, reflecting “between-group differences,” such as different schools). All observations were concatenated into vector form, and the model is as follows:

$$y = X\beta + Zu + \varepsilon \tag{6}$$

In this context, y denotes the $n \times 1$ response variable vector (teacher digital competency value-added VA); X denotes the fixed effects design matrix; β denotes the fixed effects parameter vector; Z denotes the random effects design matrix; $u \sim N(0,G)$ is the random effects vector, where G is its covariance matrix; $\varepsilon \sim N(0,R)$ is the error vector, where R is its covariance matrix.

The model fitting results are shown in table 3, which displays the estimated coefficients, standard errors, Z values, P values, and 95% confidence intervals for the fixed effects, as well as the variance components for the random effects. As shown in Table 3, the intercept term is statistically significant (P<0.05). However, for individual teacher attributes such as gender, academic title (professor, lecturer), age, years of experience, and pre-DC score, the P-values are consistently above 0.05, indicating that their estimated effects on digital competence value-added are not statistically significant in this hierarchical linear model.

Table 3 Mixed Linear Model Regression Results

No. Observations:	480			Method:		REML
No. Groups:	12			Scale:		8.9470
Min. group size:	40			Log-Likelihood:		-1215.3057
Max. group size:	40			Converged: Yes		
Mean group size:	40.0					
	Coef.	Std	.Err.	Z	P>|z| [0.025	0.975]
Intercept	4.132	1.806	2.288	0.022	0.593	7.671
gender[T.male]	-0.014	0.274	-0.050	0.960	-0.551	0.524
title_rank[T. professor]	-0.022	0.341	-0.064	0.949	-0.689	0.646
title_rank[T. lecturer]	-0.091	0.335	-0.271	0.787	-0.747	0.566
age	0.012	0.015	0.786	0.432	-0.017	0.040
years_experience	-0.007	0.014	-0.470	0.638	-0.034	0.021
pre_DC_score	0.010	0.027	0.369	0.712	-0.043	0.063
Group Var	0.021	0.036				

In order to more intuitively demonstrate the value-added performance of teachers' digital competence at various universities, a line chart showing the average digital competence improvement trends of teachers at various universities was created, as shown in Figure 2.

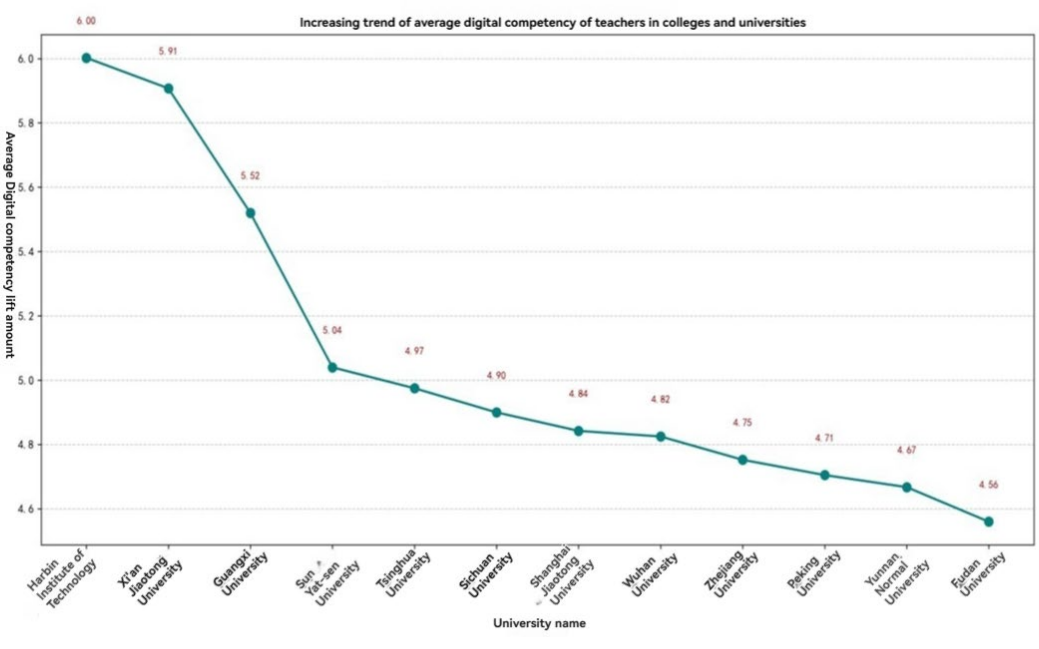

Figure 2 Trends in the improvement of average digital competence among university teachers

The chart clearly illustrates the average level of digital competency value-added (VA) among faculty members at 12 universities. As shown in the chart, the average VA scores of faculty members at most universities are concentrated between 4.5 and 6.0. Although the overall differences are relatively small, there are still notable ranking disparities. For example, Harbin Institute of Technology (6.00 points), Xi'an Jiaotong University (5.91 points), and Guangxi University (5.52 points) have the highest average VA scores, indicating that these universities have achieved significant results in enhancing faculty digital competencies, which may be closely related to their effective training mechanisms or digital resource development. In contrast, universities such as Fudan University (4.56 points) and Yunnan Normal University (4.67 points) rank relatively lower, indicating that they still have room for improvement in terms of teacher digital competency value-added.

In summary, although objective differences in value-added performance exist among universities, the fluctuations are not significant, which aligns with the results of the hierarchical linear model showing smaller Group Var values. The relatively small 'Group Var' values (0.021 and 0.036) suggest limited variance in digital competence value-added across different university groups. While this points towards individual-level factors being more dominant in explaining variance, the statistical significance of these group-level variances could not be definitively assessed from the current output.

2.3 Analysis of the Promoting Role of Individual Teacher Attributes Based on a Multivariate Linear Regression Model

To explore the relationship between individual teacher attributes and digital competency value-added, a multiple linear regression (MLR) model was used. Multiple linear regression is used to analyze the linear relationship between a dependent variable and two or more independent variables. Its basic form can be expressed as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \cdots + \beta_k x_k + \varepsilon \tag{7}$$

Among these, y represents the dependent variable, which is either teacher digital competency value-added (VA) or teacher digital attitude (digital_attitude); β_0 denotes the intercept term, indicating the expected value of the dependent variable when all independent variables are set to 0; $x_i(i = 1,2,3, \cdots, k)$ represents the independent variables, which include various individual attributes of teachers (such as age, training duration, number of research papers, digital attitude, pre-test scores, etc.) and categorical variables (such as gender, professional title, region, and whether the institution is a "Double First-Class" university); $\beta_i(i = 1,2,3, \cdots, k)$ represents the partial regression coefficient, indicating the average change in the dependent variable when the corresponding independent variable changes by one unit, while all other independent variables remain constant; ε is the error term, representing the random variation that the model cannot explain.

Table 4 Mixed Linear Model Regression Results

R^2	0.0887
Intercept	9.7067
cat__gender_male	0.6640
cat__title_rank_professor	0.5183
cat__title_rank_ lecturer	0.0809
cat__region_E	-0.2061
cat__region_W	-0.1834
num__age	0.0049
num__annual_training_hours	0.0658
num__sci_papers_last3yrs	0.2444
num_.digital_attitude	-0.1883
num__pre_DC_score	-0.1105
num__is_double_first_class	0.0421

The multiple linear regression model quantifies the independent contributions of each explanatory variable to the dependent variable and evaluates the overall goodness of fit of the model using the R² value.

To directly quantify the impact of individual teacher attributes on the added value of digital competence, a multiple linear regression model was constructed, with the model fitting results shown in Table 4. The in-sample R^2 of this multiple linear regression model is 0.0887, indicating that the model explains approximately 8.87% of the variance in the dependent variable VA. While the explanatory power is limited, this model can provide insights into the observed directions and relative magnitudes of the associations between individual teacher attributes and digital competence value-added. It is important to note that the statistical significance (p-values) for the coefficients in Table 4 were not available in the model output, thus preventing definitive conclusions regarding the statistical significance of these relationships.

To intuitively illustrate the size of each characteristic coefficient and its impact on VA, we analyze the coefficients in Figure 3 and Table 4 and find that: Male teachers (coefficient 0.6640) show a higher average digital competency value-added compared to female teachers. Similarly, professors (coefficient 0.5183) tend to have a stronger upward trend in performance. Teachers with a higher number of research papers in the past three years (coefficient 0.2444) appear to be associated with a higher tendency for digital competence value-added growth, suggesting a positive correlation between research activity and digital technology application capabilities. However, as noted, the statistical significance of these observed relationships cannot be confirmed from the provided output; Teachers in eastern (cat_region_E, coefficient -0.2061) and western (cat_region_W, coefficient -0.1834) regions have lower digital competence value-added growth compared to those in central regions; Teachers with positive digital attitudes (num_digital_attitude, coefficient -0.1883) or high pre-test scores (num_pre_DC_score, coefficient -0.1105) have limited potential for improvement, consistent with the "compensation effect" logic; Age has a small coefficient (num_age, 0.0049), while training duration (num_annual_training_hours, 0.0658) has a positive impact, indicating that training investments have a positive effect.

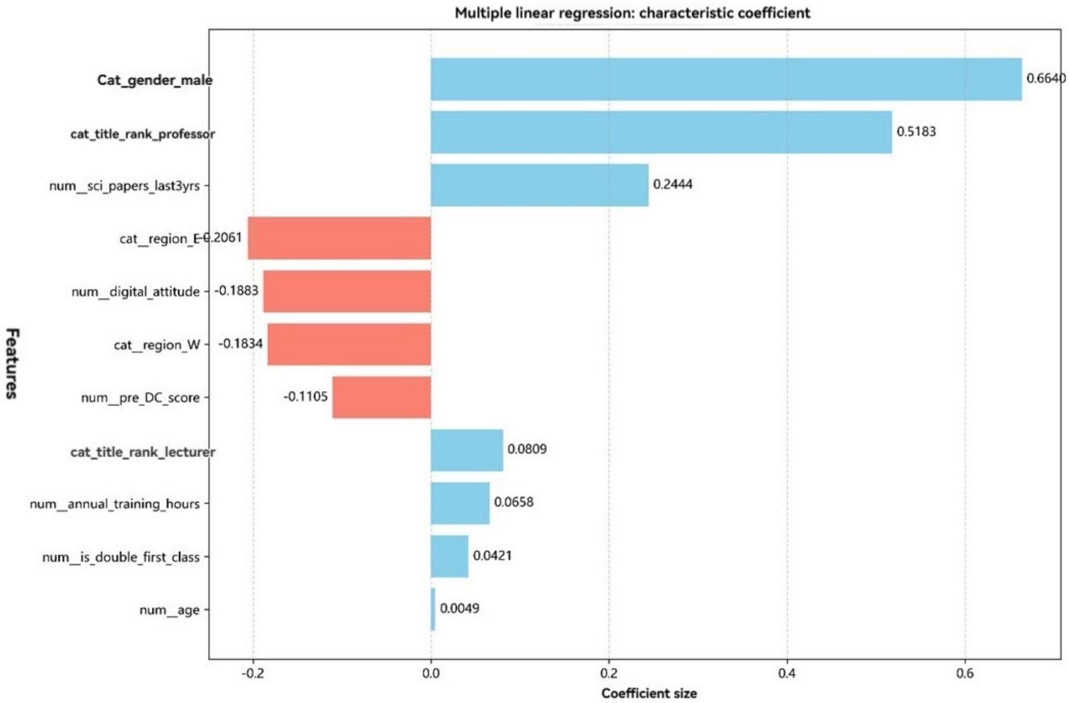

Figure 3 Multivariate linear regression feature coefficient data

Comprehensive model analysis shows that individual teacher attributes (such as gender, professional title, research output, and digital attitude) are key drivers of digital competence value-added, especially demonstrating a "compensatory effect." In contrast, macro-level contextual factors such as region and school type have limited influence. Therefore, improving digital competence will promote the quality of talent cultivation by optimizing teaching practices.

To comprehensively support the rapid development and enhancement of digital competency among university faculty, this plan proposes a systematic set of comprehensive measures in accordance with the requirements of Issue 4. These measures can be summarized as: “One Ecosystem, Two Main Threads, Three Engines, and Four Supports,” specifically outlined as follows:

(1) One Ecosystem. Comprehensively construct a digital education framework, which encompasses the development and enhancement of intelligent teaching infrastructure as well as an integrated digital teaching and learning platform.

(2) Two Main Threads. We should fully integrate capability development and value-added evaluation, which involves using precise assessment as a foundation to continuously enhance teachers' capabilities through customized training and innovative practices.This is combined with national evaluation guidelines to establish a data-driven, process-and-outcome-focused value-added evaluation system, quantifying value-added outcomes to sustainably incentivize professional growth.

(3) Three Engines. Strategic policy guidance, collaborative innovation practices, and incentive feedback mechanisms drive the continuous improvement of teachers' capabilities.

(4) Four Pillars. Data intelligent analysis, visualization feedback, security safeguards, and PDCA (Plan-Do-Check-Act) closed-loop evaluation ensure that policies are effectively implemented, outcomes are guaranteed, and iterative optimization is achievable.

3. Conclusion

This study focuses on the evaluation of digital competence among university teachers in the context of educational digital transformation. Through a series of research methods and the construction and analysis of models, this study has made preliminary findings in several areas. Regarding the construction of the evaluation system, this study established a multi-dimensional evaluation indicator system using the Delphi method and the Analytic Hierarchy Process (AHP), based on industry standards and teacher characteristics, ensuring its scientific rigor and reliability. In terms of influencing factor analysis, this study employed hierarchical linear models and multiple linear regression models to explore the potential impact of institutional resources and individual teacher attributes on the enhancement of digital competence. The results of the hierarchical linear model showed that the fixed effects of individual teacher attributes examined in this study (such as gender, academic title, age, years of experience, and pre-DC score) did not reach statistical significance. The multiple linear regression model, however, revealed observed positive association trends between some individual attributes (such as academic title and research output) and the value-added development of digital competencies. However, due to the lack of statistical significance testing, the certainty of these associations requires further validation. Furthermore, the explanatory power of the multiple linear regression model was limited (R^2 of 0.0887), indicating that other important influencing factors not captured by the model may exist. Regarding strategy formulation, based on the aforementioned model analysis results and a comprehensive consideration of teachers' digital competence development, this study proposed a systematic set of improvement strategies and educational digital empowerment measures, namely "one ecosystem, two main threads, three engines, and four supports." These measures cover aspects such as the construction of a digital education ecosystem, the integration of capability cultivation and evaluation, and strategic policy guidance. The findings of this study contribute to effectively promoting the synergistic development of institutional growth, teacher development, and national policies, providing a theoretical framework and practical direction for the digital transformation of higher education, and offering references for enhancing university teachers' digital competence.

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