International Journal of Computer Information Systems and Industrial Management Applications
ISSN 2150-7988 Volume 18 (2026) pp. 1-13

https://doi.org/10.70917/ijcisim-2026-0030
Article

Quantitative Research on the Influence Mechanism of Digital Transformation of Universities on Regional Economic Competitiveness Based on Multivariate Statistical Analysis

Yan Hong *

Division of Development and Planning, Xi'an Medical University, Xi'an 710021, Shaanxi, China; hongyan@xiyi.edu.cn

Abstract: Aiming at the problems of insufficient systematic assessment system of digital maturity of colleges and universities and in-depth exploration of regional impact heterogeneity in existing research, this paper constructs a maturity assessment model containing three dimensions of digital strategy, digital technology, and digital capability. Based on the panel data of 25 provinces in China from 2015 to 2024, the hierarchical analysis method is used to determine the weights of the indicators. Combining the spatial Durbin model and the fixed-effects model, the path of the influence of the digital maturity of colleges and universities on the competitiveness of the regional economy and the characteristics of regional heterogeneity are systematically revealed. The overall digital maturity of colleges and universities is at the medium-high level (the mean value is 0.61), close to the governance level, but the differences between regions are significant. The EDM coefficient of the western region reaches 10.389 (t=2.753, 1% significant), far exceeding that of other regions, while the eastern region focuses on synergistic effects with industrial upgrading, the central region focuses on optimization of resource allocation, and the northeastern region is limited by traditional path dependence.

Keywords: digital maturity of universities; regional economic competitiveness; spatial Durbin model; fixed effects model

1. Introduction

In recent years, digital transformation has become a focus of attention in the global education field [1-2]. The Chinese government has integrated education, science and technology, and human resources into a “trinity” arrangement, and clearly put forward the important initiative of “promoting the digitalization of education”, which points out the direction for the future development of digitalization in education [3]. Generally speaking, digital transformation requires the application of modern technology in the organization's business processes to achieve its goals and improve efficiency [4]. Universities are committed to the digital transformation of education for two main purposes, firstly, to provide high quality standards of educational services and to develop human resources capable of responding to the needs of the global industry [5]. The second is to develop a competitive advantage in the global education sector [6]. Based on this, how to make the education system adaptable to changing needs by reshaping it has become an important proposition for studying the digital transformation of university education.

Currently, the digital transformation of Chinese colleges and universities is still in the primary stage, the understanding of the problems faced by the digital transformation of education is not clear enough, and the lack of a guiding framework for the implementation of the digitalization of education is still the main bottleneck that restricts the digital transformation of colleges and universities [7-9]. As a whole, there are still some obstacles for Chinese universities in the process of digital transformation, such as the technology and products of education informatization are mostly imported, which cannot move towards self-reliance in science and technology [10]. The existing educational theories are difficult to guide the complex teaching practices in the digital era, resulting in the inability to fully digitize [11]. Meanwhile, with the advancement of Chinese-style modernization, the enhancement of regional economic competitiveness depends more and more on high-quality talent cultivation and innovation-driven capabilities [12-13]. However, the traditional fragmentation of university education and industrial development has led to a disconnect between the effect of talent cultivation and the actual demand, which restricts the competitiveness enhancement of regional economy [14]. The digital transformation of colleges and universities as a new education model can effectively dock the market demand, improve the quality of talent training, and provide strong support for regional economic development [15].

This paper firstly constructs a multidimensional and multilevel digital maturity assessment model for colleges and universities, covering dimension design, index optimization and weight calculation. Based on the panel data of 25 provinces in China from 2015 to 2024, empirical investigation is carried out through variable selection, model setting and regression analysis. Combining the spatial econometric model and fixed effect model, the direct effect and spatial spillover effect of the digital maturity of universities on regional economic competitiveness are revealed. Through the regional heterogeneity analysis, the differentiation mechanism of the digitalization of universities in different economic development stages is identified.

2. Construction and Application of a Digital Maturity Assessment Model for Higher Education Institutions

In the wave of global digital transformation, digital economy has become the core kinetic energy driving economic growth. As a key node of the knowledge innovation system, the digitization level of colleges and universities not only directly affects their own education quality and research capacity, but also contributes to the competitiveness of the regional economy through the path of technological spillovers, talent delivery and industrial synergies. In addition, the gradient difference in the level of regional economic development may lead to the heterogeneity of the path of university digitization, but the empirical test of this in the existing research is still weak.

2.1. Digital Maturity Assessment Model for Higher Education Institutions

UDMAM makes comprehensive consideration according to the digital development process and divides the digital maturity into 5 levels to form a three-dimensional model. The framework of the digital maturity assessment model for universities is shown in Figure 1, which builds capacity for digitization of universities in an all-round way.

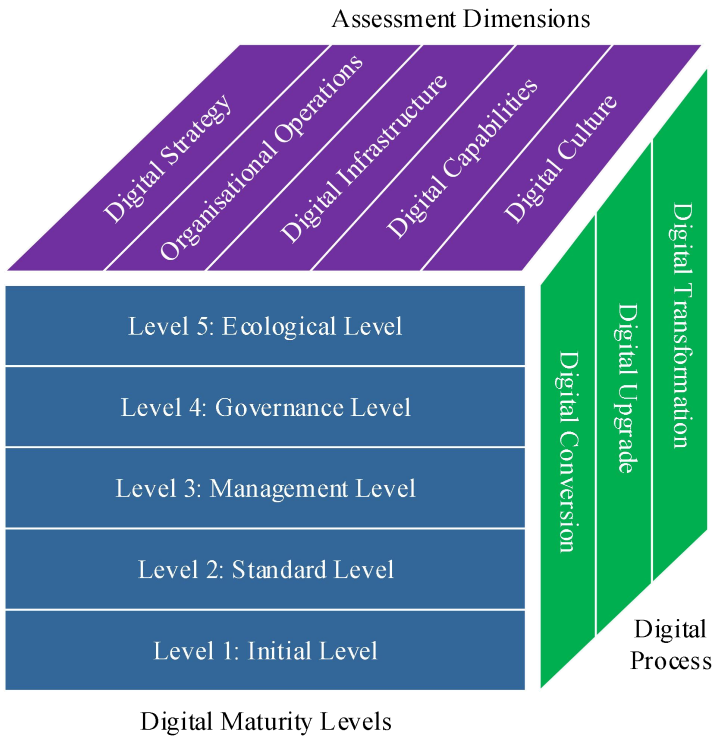

Figure 1. Framework of the Digital maturity assessment model.

(1) Digital Maturity Assessment Dimensions

The digital maturity assessment dimensions specify the capabilities that universities should have in digital construction, including digital strategy, organizational operation, digital infrastructure, digital capability and digital culture. By quantifying the assessment dimensions, the ability to realize each indicator is then assessed.

(2) Digital Maturity Level Dimensions

Digital maturity is divided into five levels: level 1 is the initial level, level 2 is the normative level, level 3 is the management level, level 4 is the governance level, and level 5 is the ecological level.

(3) Digitalization process dimensions

The digitalization process consists of 3 stages: digital conversion, digital upgrading, and digital transformation. The maturity levels corresponding to different digitalization process stages have different connotations.

2.2. Optimization of the Assessment Model

After the preliminary construction, although this paper has formed a digital maturity assessment model of college education, its indicator system still has some deficiencies, mainly manifested as follows: (1) Although the expert feedback suggestions were collected through the Delphi method survey and the indicator adjustments were made, some of the indicators are still inconsistent with the experts' opinions. This indicates that there are understanding biases or cognitive differences among different experts in the process of constructing the indicator system. (2) Although the names of indicators at all levels in the assessment model have been determined, the importance of different indicators has not been fully clarified, which may affect the accuracy and reliability of the assessment results. In this regard, it is necessary to further optimize the assessment model of digital maturity of higher education to ensure the consistency of experts' opinions, especially to clarify the weights of the indicators in order to improve the scientificity and credibility of the assessment model.

(1) Analysis of the degree of expert authority and the consistency of opinions

1) Analysis of the degree of expert authority

In order to ensure the authority of the index system, this paper uses the expert authority coefficient to assess the degree of expert authority. The expert authority coefficient (Cr) is equal to the arithmetic mean of the coefficient of familiarity (Cs) and the coefficient of the basis of judgment (Ca), i.e., $Cr = (Cs + Ca)/2$. Generally speaking, when the value of Cr is ≥0.7, the research results can be considered reliable. After calculation, the Cr value of the first batch of expert consultation = 0.901, and the Cr value of the second batch of expert consultation = 0.918. Thus, it can be seen that the expert opinions in the process of constructing the digital maturity assessment model of college education in this study have strong authority and reliability.

2) Analysis of the coordination of expert opinions

In order to comprehensively evaluate the coordination of expert opinions, this paper adopts the Kendall's W coefficient, which ranges from 0 to 1. The larger the value, the more the expert opinions converge. At the same time, this study conducts Pearson chi-square test on Kendall's W coefficient, if $p < 0.05$, it indicates that there is consistency in the rating opinions of the survey.

In the first batch of expert consultation, the Kendall's W coefficient values of experts' ratings of the overall dimensions, first-level indicators, and the importance of second-level indicators were 0.168, 0.346, and 0.311, respectively; and the Pearson's chi-square test results showed that $p > 0.05$, which indicated that there was low coherence of experts' opinions on the overall dimensions in the first batch of expert consultation that the scoring opinions of the survey were not coherent. Accordingly, this study combined and adjusted the overall dimensions and first-level indicators, while combining and optimizing the second-level indicators.

In the second batch of expert consultation, the Kendall's W coefficient values of the experts' ratings of the importance of the first-level, second-level and third-level indicators were 0.701, 0.618 and 0.583, respectively, which indicated that the harmonization of the experts' opinions on the first-level indicators was high, while the harmonization of their opinions on the second-level and third-level indicators was medium; and the Pearson chi-square test shows $p < 0.05$, indicating that the experts' opinions on the scoring of the indicator system converge.

The results of the above data analysis show that after two rounds of survey and analysis, the experts' evaluation of the indicators in the digital maturity assessment model of university education tends to be consistent, thus verifying the stability and reliability of the assessment model.

2) Calculating and Determining the Weights of Indicators

In order to improve the comprehensiveness and accuracy of the digital maturity assessment model of college education, this paper first asks experts to rate the importance of indicators in the second batch of expert consultation, and summarizes the initial scores of experts. After that, the initial results are fed back to the experts again, who are asked to weight or rank the indicators by two-by-two comparison to determine the relative importance of each indicator. Finally, the expert opinions were converted into numerical values, and the weights of each indicator were calculated using hierarchical analysis. In order to ensure the credibility and accuracy of the expert opinion, this paper also conducted a consistency test on the weights of the indicators calculated by hierarchy to determine the final weights of the indicators at all levels and to form a complete assessment model of the digital maturity of college education.

(1) Judgment Matrix Generation of Indicator Weights for Digital Maturity Assessment of College Education

By comparing the importance of indicators at all levels, this paper generates a series of judgment matrices. The judgment matrix is constructed using the 1~9 scale method, which means that the comparison of the importance between two indicators is expressed in numbers, where "1" means that the two indicators have the same importance, and "9" means that one indicator is far more important than the other. These scales are mainly used to invite experts to compare and rate the indicators at all levels of digital maturity, after which the indicators are presented in accordance with the degree of importance, forming a hierarchical model that includes the target level, guideline level, and indicator level, so as to generate the final judgment matrix.

2) Judgment Matrix Correction of Indicator Weights for Digital Maturity Assessment of College Education

In order to eliminate the potential bias of expert evaluation, this study used the consistency test to correct the judgment matrix, mainly identifying and eliminating those data with too high consistency ratios (CR), and the final number of experts included in the analysis was 30 (all CR values were less than 0.10). It should be noted in particular that for judgment matrices with CR values slightly higher than 0.10, this study mainly adopts two methods for comprehensive treatment: asking experts to correct the relative scores of the corresponding indexes and automatically correcting the judgment matrices using Yaanp software.

3) Determination of the weights of indicators for assessing the digital maturity of university education

For the judgment matrix that passes the consistency test, this study adopts the inverse matrix method to determine the weight of each indicator: first, the judgment matrix A composed of expert indicator scores is entered into Yaanp for layer-by-layer analysis; subsequently, the matrix A is row-normalized, i.e., the elements of each row i are divided by the sum of the elements of the row, so that the sum of the elements of each row is 1, and the normalized judgment matrix obtained is $A_{\_norm}$, which is calculated as shown in equation (1). Where, $j = 1, 2, 3, \cdots, n$, n denotes the order of the judgment matrix. Finally, the inverse matrix $A_{\_norm}^{-1}$ of matrix $A_{\_norm}$ is calculated, and then the inverse matrix is calculated by row normalization, and the obtained value is the weight, which is calculated as shown in equation (2). Where, $j = 1, 2, 3, \cdots, n$, ω_i denotes the weight of the i th indicator, and n denotes the number of indicators.

$$\hat{a}_{ij} = \frac{a_{ij}}{\sum_{j=1}^{n} a_{ij}} \tag{1}$$

$$\omega_i = \frac{\sum_{j=1}^{n} \hat{a}_{ji}}{n} \tag{2}$$

After the above processing, this paper optimizes the digital maturity assessment model of college education, and obtains the indicators and weights that pass the consistency test. Table 1 shows the digital maturity assessment model of university education. The evaluation model consists of three first-level indicators, namely digital strategy, digital technology, and digital capability. Specifically, there are 3 second-level indicators and 8 third-level indicators under the "Digital Strategy", 2 second-level indicators and 7 third-level indicators under the "Digital Technology", and 3 second-level indicators and 8 third-level indicators under the "Digital Capability".

Table 1. Maturity Assessment Model Indicators and Their Weights.

First-level indicator (Weight)	Secondary indicators (Weight)	Third-level indicators (Weight)
Digital strategy (0.3028)	Digital investment (0.2957)	Digital management system (0.0572)
		Digital funding input (0.0323)
	Digital decision-making (0.4084)	Digital strategic planning (0.0445)
		Digital management strategy (0.0218)
		Digital standard accuracy (0.0574)
	Digital business (0.2959)	Digital business scope (0.0121)
		Numbers and Business Scale (0.0348)
		Depth of digital business (0.0427)
Digital technology (0.3517)	Digital environment (0.6937)	Local area network and WiFi (0.0698)
		Digital hardware (0.0882)
		Digital software (0.0246)
		New-generation technologies such as artificial intelligence (0.0317)
		Digital storage (0.0297)
	Digital Security (0.3063)	Digital network security guarantee (0.0582)
		Digital risk protection (0.0495)
Digital capability (0.3455)	Digital management (0.4724)	Digital technology management (0.0694)
		Digital platform management (0.0388)
		Digital resource management (0.0550)
	Digital teaching and research	Organization of digital training for teachers

	(0.3318)	(0.0424)
		Teachers' willingness to apply digitalization (0.0218)
		The effectiveness of teachers' application of digitalization (0.0504)
	Digital learning (0.1958)	Digital student support services (0.0332)
		The effectiveness of students' digital learning (0.0345)

2.3. Construction of the Assessment Model

2.3.1. Calculation of the Superiority of the Evaluation Indicators at Level 1

The canonical correlations of the first-level evaluation indicators with respect to their corresponding second-level evaluation indicators are, respectively:

$$k_1(M_i) = \begin{pmatrix} k_{11}(M_i) \\ k_{12}(M_i) \\ k_{13}(M_i) \end{pmatrix} \tag{3}$$

$$k_2(M_i) = \begin{pmatrix} k_{21}(M_i) \\ k_{22}(M_i) \end{pmatrix} \tag{4}$$

$$k_3(M_i) = \begin{pmatrix} k_{31}(M_i) \\ k_{32}(M_i) \\ k_{33}(M_i) \end{pmatrix}, (i = 1, 2, \cdots, n) \tag{5}$$

The superiority values of the level 1 evaluation indicators are respectively:

$$C_1(M_i) = (\alpha_{11}, \alpha_{12}, \alpha_{13})(k_{11}(M_i), k_{12}(M_i), k_{13}(M_i))^T = \sum_{j=1}^{3} \alpha_{1j} \cdot k_{1j}(M_i) \tag{6}$$

$$C_2(M_i) = (\alpha_{21}, \alpha_{22})(k_{21}(M_i), k_{22}(M_i))^T = \sum_{k=1}^{2} \alpha_{2k} \cdot k_{2k}(M_i) \tag{7}$$

$$C_3(M_i) = (\alpha_{31}, \alpha_{32}, \alpha_{33})(k_{31}(M_i), k_{32}(M_i), k_{33}(M_i))^T = \sum_{j=1}^{3} \alpha_{3j} \cdot k_{3j}(M_i) \tag{8}$$

2.3.2. Calculate the Combined Maturity Superiority

Utilizing superiority expressions

$$
\begin{aligned}
C(M_i) &= \left(\alpha_1,\alpha_2,\alpha_3,\alpha_4,\alpha_5,\alpha_6\right) \\
&\cdot\left(C_1(M_i),C_2(M_i),C_3(M_i)\right)^T \\
&= \sum_{l=1}^{3}\alpha_l\cdot C_l(M_i)
\end{aligned}
\tag{9}
$$

Find the composite superiority of digital campus construction maturity of each university $M_i(i=1,2,\cdots,n)$.

Compare the composite superiority value of digital campus construction maturity of $M_i(i=1,2,\cdots,n)$: if $C(M_0)=\max_{h\in\{1,2,\cdots,n\}}\{C(M_h)\}$, then M_0 for universities with high maturity of digital campus construction.

Simulation is performed by computer to reduce the amount of computation and enhance the practicality of the method in the paper.

2.4. Digital Maturity Assessment for Higher Education Institutions

The maturity of digital campus development in provinces A , provinces B , and provinces C was selected for evaluation, and the methodology in the text was used to assess and rank them.

For convenience, the term is still used:

$$
I=\{I_1,I_2,I_3\} \tag{10}
$$

Indicates a level 1 evaluation indicator. Take:

$I_1=\{I_{11},I_{12},I_{13}\}$, $I_2=\{I_{21},I_{22}\}$, $I_3=\{I_{31},I_{32},I_{33}$ denote the level 2 evaluation indicator.

Based on the available information and research data, the quantitative values of A, B and C on the level 2 evaluation indicators were determined as shown in Table 2. Taken together, Province B has the highest maturity level of digital campus construction.

Table 2. A, B and C values of the second-level evaluation indicators.

Province	A	B	C
I_{11}	0.68	0.71	0.63
I_{12}	0.37	0.55	0.49
I_{13}	0.72	0.71	0.68
I_{21}	0.83	0.85	0.81
I_{22}	0.62	0.71	0.66
I_{31}	0.78	0.75	0.77
I_{32}	0.63	0.66	0.65
I_{33}	0.59	0.64	0.68

3. Empirical Analysis of the Impact Mechanism of Digital Transformation of Higher Education Institutions on the Competitiveness of the Regional Economy

3.1. Variable Selection and Data Sources

The impact of the digital maturity of universities on the regional economic development level is investigated from a spatial perspective based on data from 25 provinces in China from 2015 to 2024.

Explained variable: regional economic development level, expressed as per capita GDP (PGDP) of each province, data from China Statistical Yearbook.

Core explanatory variables: digital maturity of universities (EDM), this paper constructs an evaluation index system from three dimensions, including digital strategy, digital technology and digital capability, to conduct a comprehensive evaluation of the digital maturity of universities. In this index system, the data come from the statistical yearbook of each province.

Control variables: this paper selects innovation capital input (ICI), regional openness level (ROL), degree of government intervention (DGI), and infrastructure level (IL) as control variables to eliminate the interference of other factors on the empirical results in the research process. Among them, innovation capital input is expressed as the ratio of regional research and development expenditure to regional GDP; regional openness is expressed as the ratio of regional merchandise import and export volume to regional GDP; the degree of government intervention is expressed as the ratio of local government fiscal expenditure to regional GDP; and the level of infrastructure is expressed as the ratio of fixed asset investment volume to regional GDP.

3.2. Descriptive Statistics of Variables

The results of descriptive statistics of variables are shown in Table 3. Where the unit of PGDP is 10,000 yuan, EDM is standardized to take values in the range of [0,1], and the units of ICI, ROL, DGI, and IL are percentages. The sample covers the panel data of 25 provinces in China from 2015-2024, with a total of 250 observations. The mean value of the explanatory variable PGDP is 65,200 yuan, indicating that the overall per capita GDP of the sample provinces is in the upper middle level. The standard deviation of 18,300 yuan reflects the gradient difference in the level of economic development between the eastern, central and western regions. The mean value of the core explanatory variable EDM is 0.61, indicating that the digital maturity of colleges and universities as a whole is at the upper middle level, close to the governance level. Among the control variables, the mean value of ICI is 2.53%, which is in line with the steady growth of R&D investment intensity in China in recent years.The mean value of ROL is 30.12%, the mean value of DGI is 24.87%, and the mean value of IL is 64.56%. The standard deviation of each variable is smaller than the mean value, and the data stability is good, which meets the prerequisites for subsequent econometric analysis.

Table 3. Descriptive statistical Results of Variables.

Variable	Variable number	Mean value	Standard deviation	Minimum value	Maximum value
PGDP	250	6.52	1.83	3.12	10.05
EDM	250	0.61	0.15	0.32	0.91
ICI	250	2.53	0.31	1.52	3.48
ROL	250	30.12	8.07	10.05	58.62
DGI	250	24.87	2.94	18.11	31.95
IL	250	64.56	4.89	52.33	73.78

3.3. Model Construction and Selection

In the construction of panel data spatial measurement model, the more common ones are the spatial lag model (SLM) considering the spatial lag term of the explanatory variables, the spatial error model (SEM) considering the spatial error lag, and the spatial Durbin model (SDM) considering the spatial lag of the explanatory variables and the explanatory variable lag, and so on. Relevant tests need to be carried out before model selection, due to the existence of spatial effects will cause the relationship between the digital maturity of colleges and universities and the level of regional economic development between the two become relatively complex, the traditional OLS regression can not reflect the impact of spatial effects, so it is necessary to carry out the LM test, to further determine the impact of the digital maturity of colleges and universities on the level of regional economic development is applicable to spatial econometric models, the original Hypothesis H_0 : there is no spatial effect on the impact of the digital maturity of colleges and universities on the level of regional economic development. Its test results are shown in Table 4.

$$
\begin{aligned}
PGDP_{it} = {} & c + \rho WPGDP_{it} + \beta_1 EDM_{it} + \beta_2 ICI_{it} \\
& + \beta_3 ROL_{it} + \beta_4 DGI_{it} + \beta_5 IL_{it} \\
& + W\left(\Phi_1 EDM_{it} + \Phi_2 ICI_{it} + \Phi_3 ROL_{it} + \Phi_4 DGI_{it} + \Phi_5 IL_{it}\right) \\
& + \varepsilon_{it}, \varepsilon_{it} \sim N(0, \sigma^2)
\end{aligned} \tag{11}
$$

In equation (11), c is the constant term; ρ denotes the coefficient of the spatial lag term of the explanatory variables, and W is the spatial weight matrix, reflecting the interdependence of individuals in space; β_i denotes the coefficient of the effect of the explanatory variables and the control variables on the economic contribution; Φ_i denotes the coefficient of the spatial lag term of the explanatory variables and the control variables ; ε is the randomized disturbance term, which obeys a normal distribution with mean 0 and variance σ^2 .

From Table 4, it can be observed that the LM tests all significantly reject the original hypothesis H_0, indicating that there is indeed a spatial effect of the impact of the digital maturity of universities on the level of regional economic development, and the spatial lag model (SLM) and the spatial error model (SEM) are both applicable to the study, so the spatial Durbin model (SDM) is used to study the spatial relationship that exists between the two.

Table 4. LM Test Results.

LM Test Results	Statistical value	P
LM err	201.686	0.002
robust LM err	119.463	0.000
LM lag	96.385	0.011
robust LM lag	5.038	0.000

3.4. Regression Results

3.4.1. Spatial Measurement Models

Based on the above findings, the three fixed effects of the spatial Durbin model were estimated and tested, and the results are shown in Table 5, where t-statistic values in parentheses are used to test for significance. "***" means significant at the 1% level, '**' means significant at the 5% level, and '*' means significant at the 10% level. Among the three effects ρ and $Sigma^2$ are significant, and the spatial Durbin model with time fixed effects is selected for empirical study below.

In the spatial Durbin model with time fixed effects, the coefficient of the economic contribution of the digital maturity of colleges and universities is 2.85 and significantly positive at the 1% level, which confirms that the digital maturity of colleges and universities has a positive promotion effect on per capita GDP. From the spatial interaction analysis $W * EDM$ passes the significance test at 1% level and the value is 1.46, which indicates that there is a positive spatial effect of university digital maturity on economic contribution. In addition, the values of $W * ROL$ and $W * DGI$ are 6.05 and 3.11 respectively, which pass the significance test at the 5% level, indicating that there is also a positive spatial effect of the level of regional openness and the degree of government intervention on the economic contribution.

Table 5. Spatial Durbin Model.

	PGDP		
	Regional fixed effect	Time-fixed effect	Double fixed effect
EDM	1.57*** (4.04)	2.85*** (9.29)	2.88*** (9.97)
ICI	13.35 (1.88)	6.12 (1.12)	3.75 (0.69)
ROL	5.13*** (5.06)	-5.11*** (-6.02)	-6.04*** (-8.47)
DGI	-0.63 (-1.85)	-1.69** (-3.69)	-2.04*** (-5.06)
IL	-0.73** (-2.95)	0.33*** (4.23)	0.32** (3.93)
W*EDM	3.68*** (4.22)	1.46*** (3.06)	4.02*** (6.18)
W*ICI	30.11* (3.12)	1.56 (0.23)	-14.23 (-0.97)
W*ROL	-3.38* (-2.33)	6.05** (5.18)	0.12 (0.08)
W*DGI	3.02*** (5.06)	3.11** (4.28)	1.46 (2.04)
W*IL	-0.11 (-0.29)	0.09 (0.21)	0.15 (0.56)
ρ	0.23* (2.11)	0.77*** (15.38)	0.04 (0.22)
$Sigma^2$	0.21*** (14.47)	0.02*** (13.53)	0.01*** (15.92)

3.4.2. Heterogeneity Analysis

Since the level of higher education and the index of high-quality economic development have obvious regionalization characteristics, this paper, based on the division of China's economic regions by the National Bureau of Statistics, analyzes the impact of the digital maturity of higher education institutions on the high-quality development of the economy in the eastern, central, western and northeastern regions of China, and establishes the corresponding model I, model II, model III, and model IV, respectively. The fixed effects regression results of the four models are calculated by Stata and shown in Table 6.

From the coefficient of the core explanatory variable EDM, there is a significant difference between different regions: the coefficient of EDM in the eastern region is 0.311 (t=0.106, 1% significant), indicating that for every one unit increase in the digitization of colleges and universities in the region, the level of economic development grows by about 0.311 units. The EDM coefficient in the central region jumps to 2.497 (t=3.972, 5% significant), showing a stronger positive contribution. The EDM coefficient in the western region reaches 10.389 (t=2.753, 1% significant), far exceeding that of other regions, reflecting that the marginal contribution of the digitization of universities in the west to economic development is particularly prominent. The EDM coefficient in the Northeast is only 0.032 (t=0.054, 1% significant), with the weakest growth effect. This difference may be closely related to the stage of regional economic development, i.e., the eastern region has a strong economic foundation, and digitization technology pulls the economy more indirectly through industrial upgrading. While the central region is in the key period of industrial transformation, the optimization effect of digitalization on resource allocation is more significant. The western region has a weak foundation in traditional industries, and the late-stage advantage brought by digitalization investment can be released centrally. In the northeast, the economic effects of digital transformation have not yet fully emerged due to the dependence on traditional industrial paths and institutional constraints.

In terms of the regional performance of control variables, innovation capital investment only passes the significance test in the east (0.012, t=0.005, 10% significant) and northeast (0.021, t=0.018, 10% significant), reflecting that the mature innovation ecology in the east and the demand for technological transformation in the old industrial bases in the northeast are more sensitive to the investment in innovation. The level of regional openness is significant in all four regions, especially in the west, where the coefficient of openness is as high as 36.367. The level of government intervention is significant in the east, west and northeast, with the coefficient in the west far exceeding that in the other regions. The level of infrastructure is significant in the east, center and west, with only the northeast having a weaker marginal effect.

Table 6. Fixed Effects Model.

Variable	Model 1	Model 2	Model 3	Model 4
PGDP	0.078*** (0.014)	100.468*** (31.586)	16.486*** (10.252)	0.197*** (0.093)
EDM	0.311*** (0.106)	2.497* (3.972)	10.389*** (2.753)	0.032*** (0.054)
ICI	0.012* (0.005)	0.603 (1.286)	1.637 (2.048)	0.021* (0.018)
ROL	0.038*** (0.017)	15.386*** (13.257)	36.367*** (7.038)	0.675*** (0.062)
DGI	0.048*** (0.023)	70.365*** (10.104)	62.586*** (13.647)	0.398*** (0.071)
IL	8.035* (0.004)	5.038*** (17.468)	8.047*** (16.368)	0.503*** (0.089)
_cons	-10.386*** (0.308)	-31.975*** (19.586)	-9.027*** (26.286)	-4.027*** (29.486)

3.4.3. Fixed Effects Models

The regression analysis was carried out using a fixed effects model, model V is the regression equation without adding any control variables, and models VI, VII, VIII and IX are the results after adding control variables sequentially. The overall regression results are shown in Table 7, and the R2 values of the above models are all greater than 0.9, which indicates that the models fit well. According to the regression results, the digital maturity of colleges and universities is significantly and positively correlated with regional economic growth, passing the 1% significance test. For every 1% increase in the digital maturity of colleges and universities, regional economic growth increases by about 0.402%. Other control variables were then added in turn, all of which passed the 1% significance test and the coefficients did not change much. The digital maturity of higher education institutions is the most contributing explanatory variable among several variables, proving that the digital maturity of higher education institutions has a positive impact on economic growth.

Table 7. Overall Regression Results.

Variable	Model 5	Model 6	Model 7	Model 8	Model 9
EDM	0.402***	0.415***	0.397***	0.384***	0.377***
ICI		0.012**	0.0113*	0.0097	0.0078

ROL			0.101***	1.286***	1.048**
DGI				-0.375*	-0.386*
IL					0.476
_cons	7.037***	7.041***	7.112***	7.156***	7.208***
R^2	0.984	0.981	0.985	0.984	0.986

4. Conclusion

This study systematically reveals the mechanism of the impact of university digitization on regional economic competitiveness and the characteristics of regional heterogeneity by constructing a model for assessing the maturity of university digitization and combining panel data from 25 provinces in China from 2015 to 2024. The main conclusions are as follows:

First, the overall digitization maturity of colleges and universities is at a medium-high level (mean value of 0.61), close to the governance level, but with significant regional differences. The EDM coefficient of the western region reaches 10.389 (t=2.753, 1% significant), far exceeding that of other regions, while the eastern region focuses on synergistic effects with industrial upgrading, the central region focuses on optimization of resource allocation, and the northeastern region is limited by traditional path dependence.

Second, innovation capital investment (ICI) passes the significance test only in the eastern (0.012, t=0.005, 10% significant) and northeastern regions (0.021, t=0.018, 10% significant). Regional Openness Level (ROL) is significant in all four regions, especially in the West where the coefficient of openness level is as high as 36.367.Degree of Government Intervention (DGI) is significant in the East, West and Northeast, with the coefficient in the West far exceeding that of the other regions. The level of infrastructure (IL) is significant in the east, center, and west, with only a weak marginal effect in the northeast.

Third, in the spatial Durbin model with time fixed effects, the coefficient of the economic contribution of the digital maturity of colleges and universities is 2.85 and significantly positive at the 1% level. From the spatial interaction analysis $W * EDM$ passes the significance test at the 1% level and the value is 1.46. In the fixed-effects model, the digital maturity of colleges and universities is the most contributing explanatory variable among the several variables, which proves that the digital maturity of colleges and universities has a positive effect on economic growth.

References

1. Kapur, R., Byfield, V., Del Frate, F., Higgins, M., & Jagannathan, S. (2018). The digital transformation of education. Earth observation open science and innovation, 25-41.
2. Tsymbal, L., & Kalenyuk, I. (2023). Digital transformation of the global education market. Baltic Journal of Economic Studies, 9(5), 266-274.
3. Duan, Y., & Zhang, Z. (2022, September). Exploring the “Trinity” Model of Training Artificial Intelligence Talents. In 2022 8th Annual International Conference on Network and Information Systems for Computers (ICNISC) (pp. 160-164). IEEE.
4. Kang, L., & Xu, X. (2025). Progress and prospect of digital transformation of higher education in China: Bibliometric and visualized analysis. Journal of Adult and Continuing Education, 31(1), 109-134.
5. Ma, X., Chen, M., & Diao, J. (2025). Pathways and outcomes of digital transformation in Chinese vocational colleges. Vocation, Technology & Education, 2(1).
6. Mohamed Hashim, M. A., Tlemsani, I., & Matthews, R. (2022). Higher education strategy in digital transformation. Education and Information Technologies, 27(3), 3171-3195.
7. Lyu, Y., Chi, T., & Zheng, X. (2024). Digital Transformation of Design Education in Chinese Universities: Trends, Challenges, and Opportunities. In SHS Web of Conferences (Vol. 181, p. 04037). EDP Sciences.
8. Miao, X., Dawod, A. Y., & Phaphuangwittayakul, A. (2023). The implications, challenges, and pathways of digital transformation of University Education in China. In Proceedings of the 7th TICC International Conference.
9. Xiao, J. (2019). Digital transformation in higher education: critiquing the five-year development plans (2016-2020) of 75 Chinese universities. Distance Education, 40(4), 515-533.
10. Zhang, Y., Zhang, M., Wu, L., & Li, J. (2025). Digital Transition Framework for Higher Education in AI-Assisted Engineering Teaching. Science & Education, 34(2), 933-954.
11. Papachashvili, N. I. N. O. (2021, May). Digital transformations and the challenges of higher education institutions. In 5th International Scientific Conference.
12. Malecki, E. J. (2017). Economic Competitiveness and regional development dynamics. Handbook of regions and competitiveness, 136-152.

13. Bahrami, F., Shahmoradi, B., Noori, J., Turkina, E., & Bahrami, H. (2023). Economic complexity and the dynamics of regional competitiveness a systematic review. Competitiveness Review: An International Business Journal, 33(4), 711-744.
14. Lane, J. E. (2012). Higher education and economic competitiveness. Universities and colleges as economic drivers: Measuring higher education's role in economic development, 1-30.
15. Krstić, M., Filipe, J. A., & Chavaglia, J. (2020). Higher Education as a Determinant of the Competitiveness and Sustainable Development of an Economy. Sustainability, 12(16), 6607.