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In-depth analysis of digital economy on regional economic structure transformation based on data mining

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Abstract The digital economy is reshaping the global economic pattern at an unprecedented speed, and has become an important force to promote the transformation of regional economic structure. Based on data mining technology, this paper deeply explores the mechanism and effect of digital economy on regional economic structure transformation. The study adopts a factor analysis model to construct an evaluation index system from four dimensions, namely digital communication infrastructure, digital network infrastructure, digital industry development level and innovation ability, to measure the development level of digital economy in a region from 2015 to 2024, and to analyze the impact of the digital economy on the structural transformation of the regional economy by combining the orthogonal least squares method. The results of the study show that: the level of digital economy development is significantly positively correlated with the transformation of regional economic structure, with a regression coefficient of 0.446, indicating that the development of the digital economy has a positive effect on promoting the proportion of tertiary industry; the analysis of regional heterogeneity shows that the impact of the digital economy on the transformation of the economic structure of the central region is most significant, with a regression coefficient of 0.701, which is significantly higher than that of the southern region, 0.532, and northern The analysis of control variables found that the level of financial development and the level of urbanization had a positive effect on economic structural transformation, while the level of education investment had a negative effect. The study provides theoretical basis and practical guidance for regions to formulate differentiated digital economy development strategies and promote the optimization and upgrading of economic structure.

Index Terms digital economy, regional economy, structural transformation, factor analysis, orthogonal least squares, heterogeneity analysis

I. Introduction

Internationally, the world is experiencing a great change that has not been seen in a century. The global governance system is accelerating the change, the international market “black swan” events are frequent, trade protectionism is obviously rising, the global economic uncertainty is increasing, and the regional economic structural transformation is facing a more turbulent international environment [1]-[3]. The transformation of regional economic structure requires a new round of scientific and technological revolution and industrial change to provide new kinetic energy [4]. Throughout the history of world development, each scientific and technological revolution and industrial change has provided a strong impetus for the transformation of regional economic structure. The information technology revolution that started after the Second World War laid the material and technological foundation for the globalization of economic development, and greatly promoted the modernization of industries and the transformation of labor force structure in various regions, but the potential to promote economic development is close to exhaustion, and it is no longer sufficient to support the transformation of the economic structure of various regions as well as the deep-level reconstruction [5]-[8]. At the same time, under the new round of scientific and technological revolution and industrial change, digital technology as a new general technology has given rise to the new momentum of digital economy, which is driving the transformation and upgrading of many traditional industries in various regions, and has become a catalyst for the transformation of the regional economic structure, a new driving force for regional economic growth and an important hand in the coordinated development of the region [9]-[12].

Under the wave of globalization and informatization, the digital economy is reshaping the global and regional economic landscape with unprecedented speed and scale. According to the latest reports of the International Telecommunication Union (ITU) and the World Economic Forum (WEF), the size of the global digital economy has exceeded $32 trillion in 2023, accounting for 43% of the global GDP. Digital economy, as an emerging economic form, is based on digital technology, with data as the key production factor, with modern information network as the carrier, through the deep integration of digital technology and the real economy, to promote the optimization and upgrading of the economic structure, to improve the economic efficiency, and to create new economic growth points [13], [14]. The rise of digital economy has not only changed the traditional production, distribution, exchange and consumption patterns, but also given rise to new industrial forms and employment patterns, such as online education, telemedicine, digital finance, intelligent transportation, etc. The rapid development of these emerging industries is promoting the transformation of the regional economic structure to a greener, smarter and service-oriented [15]-[19].

At the same time, the application of digital technology has accelerated the upgrading and transformation of traditional industries, improved production efficiency, reduced costs, and enhanced the quality of products and services, providing a strong impetus for the optimization and upgrading of regional economic structure [20]-[22]. However, the rapid development of digital economy has also brought new challenges such as data security, privacy protection, digital divide, and employment structure adjustment, etc. How to effectively deal with these challenges while enjoying the digital dividend has become an urgent problem in the current transformation of regional economic structure [23]-[26]. Therefore, an in-depth study of the driving mechanism of the digital economy on the transformation of regional economic structure not only helps people to better understand the internal logic of the digital economy, but also helps to formulate more effective policies to guide the healthy and sustainable development of the digital economy and promote the optimization and upgrading of regional economic structure.

As an important engine of economic development in the new era, digital economy is profoundly changing the global economic pattern and regional development mode. The rapid progress of digital technology has led to fundamental changes in the flow and processing of information, and data and information have become key production factors, promoting the continuous optimization and upgrading of economic structure. At present, a new generation of digital technologies such as big data, cloud computing and artificial intelligence are fully penetrating into all fields of economy and society, which not only give rise to new industries, new forms and new modes, but also profoundly affect the transformation and upgrading paths of traditional industries, and become the core force driving the transformation of regional economic structure. The digital economy injects new vitality into the regional economy by reducing information asymmetry, optimizing resource allocation, and enhancing production efficiency. Regions have also taken the development of digital economy as an important strategy to enhance regional competitiveness and promote high-quality development. However, due to the differences in digital infrastructure, industrial foundation, and innovation capacity among regions, there are obvious differences in the mechanism and effect of digital economy on the transformation of regional economic structure. Such differences are not only reflected in the overall level, but also in the selection of specific paths and modes, which puts forward higher requirements for the formulation of regional economic development strategies. However, existing studies mostly focus on the measurement of the level of digital economy development or the case analysis of a single region, and lack a systematic analysis of the intrinsic mechanism of the digital economy affecting the structural transformation of the regional economy, especially the exploration of regional heterogeneity is still insufficient. An in-depth understanding of the path of the digital economy's impact on regional economic structural transformation and regional differences is of great significance for regions to formulate precise digital development strategies and promote the coordinated development of regional economies.

Based on this, this study first systematically analyzes the four major mechanisms of digital economy-driven regional economic structural transformation from the theoretical level: the mechanism of technological innovation, the mechanism of resource allocation optimization, the mechanism of industrial integration and upgrading, and the mechanism of spatial effect release, and constructs a complete theoretical framework. In the empirical part, the study adopts the factor analysis method to construct an evaluation system by selecting 17 indicators from four dimensions: digital communication infrastructure, digital network infrastructure, digital industry development level, and innovation ability, to measure the digital economy development level of the sample region from 2015 to 2024, and applies the orthogonal least squares (OLS) method to control the proportion of the regional tertiary industry as the explanatory variable, the the level of financial development, the level of urbanization, the level of education investment and the level of government support to analyze the impact of the digital economy on the structural transformation of the regional economy. In addition, the study conducts a heterogeneity test according to the division of northern, central and southern regions to explore the differentiated impact of the digital economy on the structural transformation of the economy in different regions, and to provide a theoretical basis and policy recommendations for the formulation of targeted digital economy development strategies in each region.

II. Mechanisms for structural transformation of the regional economy driven by the digital economy

II. A.Mechanisms for technological innovation

The booming digital economy is reshaping the global economic landscape with unprecedented depth and breadth, the core of which lies in the efficient utilization of data and information. This core driving force has not only accelerated the pace of technological innovation, but also profoundly touched off a profound change in the structure of the regional economy. In this wave of transformation, big data, cloud computing, artificial intelligence and other cutting-edge digital technologies, like a powerful engine, have opened up a new growth channel for the regional economy.

At the same time, the digital economy has significantly lowered the threshold of technological innovation, and enterprises are able to obtain powerful computing power and rich data resources at a lower cost, thus getting rid of the dependence on asset-heavy infrastructure and focusing on the core innovation of products and services. In addition, the digital economy has accelerated the transformation and upgrading of traditional industries and technology iteration with its powerful technology driving force. The wide application of IoT technology enables traditional manufacturing industries to realize real-time monitoring and intelligent optimization of the production process, which effectively improves the efficiency of resource utilization and the level of production management, while the introduction of blockchain technology brings about a revolutionary change in the traditional financial industry in terms of transaction transparency and security, and strengthens the stability and risk-resistant capability of the financial system.

II. B.Mechanisms for optimizing resource allocation

In the era of digital economy, by breaking down the information barriers and geographical limitations under the traditional economic model, it is possible to realize accurate matching and efficient utilization of resources on a wider scale, and inject new vitality and growth momentum into the regional economy. Specifically, by building a highly interconnected network platform, the digital economy greatly improves the transparency and circulation speed of information. In the traditional economic system, information asymmetry is a key factor restricting the effective allocation of resources. Enterprises, individuals and governments are often unable to make optimal decisions due to the lack of timely and accurate information, leading to resource mismatch and inefficiency. The rise of the digital economy, especially the widespread application of big data, cloud computing, the Internet of Things and other technologies, has made it possible to rapidly collect, process and analyze huge amounts of data, providing strong information support for the optimal allocation of resources.

II. C.Mechanisms for industrial integration and upgrading

Through technological penetration and integration, the digital economy has broken down the barriers between traditional industries and promoted in-depth integration between industries. In this process, digital technologies such as big data, cloud computing, artificial intelligence and the Internet of Things have become a bridge connecting different industries, enabling traditional industries to realize transformation and upgrading with the power of information technology. The digital economy also promotes the upgrading and reconstruction of the industrial chain, and promotes the development of industries to high-end and intelligentization. The digital economy realizes the seamless connection between equipment, products and users through the construction of new infrastructure such as industrial Internet platforms and intelligent manufacturing systems, enabling all links in the industrial chain to share data and work together in real time.

II. D.Mechanisms for releasing space effects

Through its unique mechanism of releasing spatial effects, the digital economy can not only promote the balanced development of the regional economy, but also promote urban-rural integration and industrial upgrading, and provide strong support for the comprehensive transformation of the regional economic structure.

With its powerful information transmission and processing capabilities, digital economy has completely subverted the traditional mode of information flow, realizing instant sharing of data resources and cross-regional integration. This feature has greatly weakened the constraints of physical space on economic development, enabling remote areas to rapidly access the global value chain and participate in international competition and cooperation. Through the extensive application of cloud computing, big data, Internet of Things and other technologies, enterprises are able to transcend geographical constraints and realize remote collaboration in production, sales, services and other links, effectively reducing transaction costs and improving market responsiveness, thus promoting the integration and balanced development of the regional economy.

The digital economy, with its unique driving mechanism, provides a strong impetus for the transformation of regional economic structure. Based on this, this paper utilizes data mining technology and adopts a factor analysis model to measure the development level of digital economy in a certain place, and then combines the orthogonal least squares (OLS) method to empirically analyze the impact of digital economy on the transformation of regional economic structure.

III. Measurement of the development level of the digital economy based on factor analysis

III. A. Factor analysis methods

III. A. 1) Basic principles

Factor analysis is designed to explain the covariance structure of a factor model using a small number of common factors. The number of factors selected is very important; too many factors and the analysis of the applied factors loses its usefulness. However, if the number of factors selected is too small, the information may be lost. There are usually the following two guidelines:

(1) The criteria for selecting public factors need to refer to the eigenvalues of the principal component vectors. Standardize the original evaluation indexes, because the variance of all the indexes we selected is 1. Assuming that the eigenvalues of the principal component vectors obtained are less than 1, then it means that the principal components can not explain any of the indexes, so when selecting the eigenvalues, we should select the principal components that are greater than or close to 1 in amount as the public factors, and discard those other principal components whose eigenvalues are much less than 1.

(2) The selection of public factors is based on the cumulative contribution rate of the variance of the principal components. The cumulative contribution rate of variance reflects the degree of retention of original information by principal components. In general, as long as the cumulative contribution rate of principal components is above 80%, it can explain the problem well, so when selecting the public factors in the process of research, attention should be paid to selecting those principal components whose cumulative contribution rate is above 80%.

III. A. 2) Mathematical models

Factor analysis is designed to explain the factor model of covariance structure using a small number of common factors, so we can use a mathematical model for the study.

Suppose there are P primitive variables which are $x_1, x_2, x_3 \cdots x_p$, where $x_i\left(i=1,2,3,\cdots p\right)$, so there are:

$$\begin{gathered} x_1 = a_{11}F_1 + a_{12}F_2 + \cdots + a_{1m}F_m + a_1\varepsilon_1 \\ x_2 = a_{21}F_1 + a_{22}F_2 + \cdots + a_{2m}F_m + a_2\varepsilon_2 \\ \cdots \\ \cdots \\ x_p = a_{p1}F_1 + a_{p2}F_2 + \cdots + a_{pm}F_m + a_p\varepsilon_p \end{gathered} \tag{1}$$

can be expressed in matrix form as:

$$X = AF + a\varepsilon \tag{2}$$

where the mean of those original variables is equal to zero, while they are standardized variables satisfying a standard deviation of 1. $F1, F2, F3 \cdots Fm$ denote the common factor variables, respectively, which are uncorrelated and all have a variance of 1. m is less than p. ε is a special factor that represents the portion of information in the original variable that cannot be explained by the common factor.

III. A. 3) Steps in factor analysis

(1) Standardize the original sample data to eliminate the influence of the scale, and at the same time establish the evaluation index system $i=1,2,3,\cdots p$ and collect the sample index data.

(2) Standardize the sample correlation coefficient matrix to form a standardized matrix, find the eigenvalues of the standardized matrix, and calculate the contribution rate of the eigenvalues.

(3) Determine the number of common factors based on the cumulative contribution rate of factors.

(4) Use the maximum variance method to find the factor loading matrix A, so as to determine the meaning of each common factor.

(5) Establish the factor score function.

III. B. Selection of indicators

According to the relevant literature and combined with the connotation of digital economy, 17 indicators were selected from four aspects, namely, digital communication infrastructure, digital network infrastructure, digital industry development level, and innovation ability, to comprehensively reflect the status of the development level of digital economy, and the evaluation index system of digital economy development is shown in Table 1.

Table 1: The evaluation index system of digital economic development

Primary indicator	Secondary indicator
Digital communication infrastructure	Mobile phone exchange capacity (10,000 units) A1
	Mobile phone penetration rate (part per hundred people) A2
Digital network infrastructure	Cable length (kilometer/square kilometer) A3
	Long distance cable length (kilometer/square kilometer) A4
	Internet broadband access port (10,000) A5
	Internet broadband access (10,000 households) A6
	Number of domain names per 1000 people A7
	Number of sites per 1,000 people A8
	The number of pages per 1,000 people A9
Digital industry development level	Information transmission, computer services and software urban unit employment number (10,000) A10
	Information transmission, computer services and software industry will be fixed assets investment (100 million yuan) A11
	The amount of telecommunications (100 million yuan) A12
	The total delivery of the express service (10,000 units) A13
Innovative ability	Total R&D personnel (person/year) A14
	R&D funds (10,000 yuan) A15
	Number of R&D projects (items) A16
	Number of patent applications A17

III. C. Factor analysis

In this paper, SPSS25.0 is used to standardize the raw data of each indicator in Table 1 for a region from 2015 to 2024, and then KMO test and Bartlett's spherical test are carried out. The test results show that the KMO test measure is 0.846, which is greater than 0.5, indicating that the degree of information overlap between the variables is high, and the Bartlett's spherical test results show that its chi-square value is large and the probability of significance is 0.000, so that the hypothesis that the variables are independent of each other should be rejected, i.e., it is considered that there is a correlation between the variables.The KMO test and the Bartlett's spherical test results indicate that these data are suitable for factor analysis modeling.

The correlation matrix and the cumulative contribution of variance of each indicator were calculated using SPSS 25.0, and the factors with eigenvalues greater than 1 were extracted. Then rotational transformation was performed to make the loading coefficients converge to 0 or 1, and the factor contribution and cumulative contribution before and after rotation were obtained. The total variance interpretation results are shown in Table 2, the cumulative contribution rate of the three extracted public factors has reached 83.318%, and these three factors are not correlated with each other, which indicates that the information contained in these three public factors is more adequate to express the original information.

Table 2: Results of the total variance interpretation

Total variance interpretation		1	2	3
Initial eigenvalue	Total	10.538	2.597	1.029
	Variance%	61.988	15.276	6.053
	Cumulation%	61.988	77.265	83.318
Extracting the load of the load	Total	10.538	2.597	1.029
	Variance%	61.988	15.276	6.053
	Cumulation%	61.988	77.265	83.318
Rotational load squared	Total	6.883	4.776	2.505
	Variance%	40.488	28.094	14.736
	Cumulation%	40.488	68.582	83.318

The three principal factors were analyzed to obtain the rotated loading matrix and component score coefficients as shown in Table 3. The contribution of the first principal factor is 40.488%, the contribution of the second principal factor is 28.094%, and the contribution of the third principal factor is 14.736%. The composite factor value F was constructed based on the principal factor scores as well as the variance contribution as follows:F=(0.40488F1 +0.28094F2 +0.14736F3)/0.83318.

From the above formula, the score of the digital economy development level of the sample area from 2015 to 2024 can be calculated, and the score of the digital economy development level is shown in Figure 1. In terms of the score, the level of digital economy development in the sample region shows an increasing trend year by year, with the overall score increasing from 2.607 in 2015 to 4.176 in 2024, which is related to the increasing level of economic development in the region in recent years, the increasing investment in education and scientific research and the importance attached to the construction of Internet infrastructure. The average level of digital economy development in the sample region from 2015 to 2024 is 3.413, which puts the region at a medium level of development.

Table 3: The load matrix after rotation and component score coefficient

Index	The load matrix after rotation			Component score coefficient		
	1	2	3	1	2	3
A1	0.176	0.839	-0.108	-0.077	0.256	-0.047
A2	0.624	0.236	0.622	-0.025	0.009	-0.288
A3	0.732	0.086	0.571	0.064	-0.056	0.185
A4	0.064	-0.223	0.865	-0.220	-0.001	0.593
A5	0.753	0.280	0.484	0.058	-0.017	0.137
A6	0.798	0.224	0.488	0.085	-0.033	0.134
A7	0.327	0.744	0.181	-0.093	0.218	0.113
A8	0.468	0.822	0.113	-0.042	0.212	0.014
A9	0.117	0.929	-0.048	-0.137	0.293	0.025
A10	0.267	0.897	0.056	-0.111	0.271	0.043
A11	0.518	0.345	0.437	-0.025	0.059	0.179
A12	0.657	0.326	0.410	0.039	0.018	0.115
A13	0.711	0.466	0.136	0.114	0.033	-0.082
A14	0.845	0.212	-0.003	0.275	-0.099	-0.269
A15	0.898	0.252	0.154	0.226	-0.072	-0.148
A16	0.939	0.241	0.082	0.271	-0.101	-0.221
A17	0.886	0.305	0.136	0.231	-0.064	-0.162

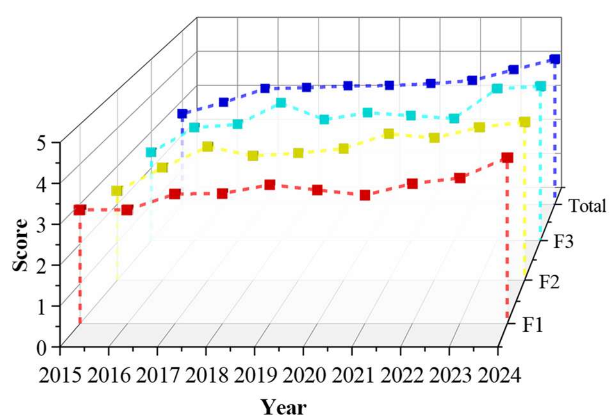

Figure 1: Scores of digital economic development

IV. Regression analysis of the digital economy on the structural transformation of the regional economy

IV. A. Orthogonal least squares

Orthogonal Least Squares (OLS) is a sparse kernel modeling method, which takes local parameter regularization (LR) and leave-one-out training error as the optimization objective, and the soft measurement model built by this method has strong generalization ability and sparsity.

It is known that $x=[x_1,x_2,\cdots,x_M]\in R^{N\times M}$ is the input variable of the system, $y\in R^{N\times 1}$ is the output variable of the system and e is the noise signal. The regression model between x and y is used for nonlinear identification by OLS method:

$$y=\hat{y}+e=\sum_{i=1}^{N}\beta_i K_\rho(x,x_i)+e=\phi\beta+e \tag{3}$$

where the kernel function $K_\rho(x,x_i)$ is a Gaussian kernel function, i.e:

$$K_\rho(x,x_i)=\exp\left(-\frac{\|x-x_i\|^2}{2\sigma^2}\right) \tag{4}$$

Solving parameter β of Eq. (3) leads to the solution of the optimization objective described in Eq. (5).

$$J=e^T e \tag{5}$$

Equation (5) essentially minimizes the mean square error (MSE) of the training data, which results in $\beta=(\phi^T\phi)^{-1}\phi^T y$.

Since $\phi\in N\times N$, when N is large, the model's operation will be more complicated and prone to dimensional catastrophe problem. Moreover, due to the existence of certain correlation between the columns of training data, $\phi^T\phi$ is very likely to be a pathological matrix, resulting in the final solution of the model parameters may have a low generalization ability and over-matching phenomenon. For this kind of problem, the OLS method decomposes ϕ by orthogonalizing it to obtain $\phi=WA$. The matrices W and A's can be computed by the improved Gram-Schimt orthogonalization method, and the final results are as follows:

$$A=\begin{bmatrix} 1 & a_{12} & a_{13} & \cdots & a_{1N} \\ 0 & 1 & a_{23} & \cdots & a_{2N} \\ 0 & 0 & \ddots & \vdots & \\ \vdots & \vdots & & 1 & a_{N-1N} \\ 0 & 0 & \cdots & 0 & 1 \end{bmatrix} \tag{6}$$

$$W=[w_1,w_2,\cdots,w_N],w_i^T w_j=0,(i\neq j) \tag{7}$$

Then the regression model can be expressed as:

$$y=Wg+e \tag{8}$$

where g is the parameter to be optimally solved by the OLS model and $g=A\beta$ and $g=[g_1,g_2,\cdots,g_N]^T$.

In Eq. (8), W is considered as the base of the model. Since the training data often have a certain correlation, the forward subset selection process is used to select $N_s(N_s \ll N)$ an irrelevant subset of the model W_{N_s} from W, i.e., only a portion of the irrelevant model bases are used to build the model, so that the model has a certain degree of sparsity. The final model thus built is:

$$y=W_{N_s}g_{N_s}+e \tag{9}$$

where g_{N_s} is the N_s term in g.

IV. B. Modeling

In order to further analyze the impact of digital economy on the transformation and upgrading of the regional economic structure in the sample area, this paper takes the regional economic structure (Res) as the explanatory variable, and uses the proportion of added value of the tertiary industry in GDP as the proxy variable. Studying the experience of indicator selection in the existing literature and the practice of related scholars, the level of digital economy development (Dig) is selected as the explanatory variable, and the score of the level of digital economy development measured above is used as the proxy variable, based on which the level of financial development (Fin), the level of urbanization (Urb), the level of education investment (Edu), and the level of government support (Gov) are selected as the control variables, respectively The regression model of digital economy on regional economic structure is constructed by using the balance of deposits of financial institutions as a proportion of GDP, the proportion of non-farming population, the proportion of education investment funds in government financial expenditure, and the proportion of government financial expenditure in GDP as proxy variables. The model is as follows:

$$ind_{it}=\alpha_0+\alpha_1 dig_{it}+k_1 fin_{it}+k_2 urb_{it}+k_3 edu_{it}+k_4 gov_{it}+\mu_{it} \tag{10}$$

where α_0 is the intercept term, α_1, k_1, k_2, k_3, and k_4 denote the regression coefficients of the explanatory variables and each control variable, and μ_{it} is the error term.

IV. C. Analysis of regression results

IV. C. 1) Basic regression results

The data used in this paper come from a regional statistical yearbook, municipal statistical yearbooks, etc. from 2015 to 2024, and for a small number of statistically missing data, linear interpolation is used to fill in the blanks, and the relevant variables are standardized to be dimensionless. Using SPSS 25.0 software, panel data regression analysis was carried out with OLS method, control variables were gradually increased, and random effects were found to be more suitable for this study through Hausman test. The results of the basic regression test are shown in Table 4, with *, **, and *** indicating significant at 10%, 5%, and 1% confidence intervals, respectively.

The number of control variables and the goodness of fit of the model change in the same direction, and with the addition of control variables, the goodness of fit of the model is improving, and the R^2 improves from 0.188 to 0.686, which indicates that the choice of control variables is reasonable and scientific. The regression results of the core explanatory variables are significantly positive ($p<0.01$), with regression coefficients of 0.431, 0332, 0.348, 0.369 and 0.446, indicating that the digital economy has a positive effect on the transformation and upgrading of the regional economic structure, and the higher the level of the development of the digital economy, the more obvious is the transformation and upgrading of the regional economic structure.

In addition, the level of regional financial development has a great positive impact on the transformation and upgrading of regional economic structure, indicating that increasing financial support, optimizing financial structure, reducing financing costs and improving capital efficiency can promote the upgrading of regional industrial structure. The level of urbanization promotes the transformation and upgrading of regional economic structure significantly, and urbanization can be beneficial to the transformation and upgrading of regional industrial structure in terms of demand, population, transportation, industrial clusters and other aspects. The positive effect of the level of government support indicates that financial support plays an important role in the transformation and upgrading of regional economic structure. And the negative effect of the regional education level reminds the talent training to match the market demand, and at the same time, we should guide the return of talents, cultivate internal and external attraction of digital economy talents, and accelerate the optimization and upgrading of economic structure.

Table 4: Basic regression test results

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
Dig	0.431	0.332	0.348	0.369	0.446
	0.001	0.000	0.004	0.001	0.002
	***	***	***	***	***
Fin		0.243	0.263	0.348	0.286
		0.002	0.003	0.005	0.005
		***	***	***	***
Urb			0.122	0.319	0.205
			0.005	0.004	0.004
			***	***	***
Edu				-0.373	-0.273
				0.001	0.003
				***	***
Gov					0.406
					0.002
					***
R^2	0.188	0.473	0.499	0.588	0.686
N	135	135	135	135	135

IV. C. 2) Heterogeneity test

By testing the sample region according to the way of north, central and south, the final regression results present the differentiated impact of the digital economy on the transformation and upgrading of the regional economic structure in the region, and the results of the sub-regional regression test are shown in Table 5. From the sub-regional regression results, the regression results of the core explanatory variables of each region are significantly positive ($p<0.01$), indicating that the digital economy has a positive impact on the transformation and upgrading of the economic structure of each region, in the order of the central region, the southern region, and the northern region, with the corresponding regression coefficients of 0.701, 0.532, and 0.487, respectively. For the reasons, the central region has a better economic foundation and stronger innovation ability, The reason is that the central region has a better economic foundation, strong innovation ability and talent gathering, which makes the development of digital economy technology fast and at a higher level, and the digital economy is fully applied to traditional industries, which makes the transformation and upgrading of traditional industries effective. The booming tourism and e-commerce industries in the southern region provide a good application platform for the development of digital economy, and the government has introduced policies to actively promote the digital transformation of enterprises. Although the northern region has a positive impact, it is relatively weak, and the indicator value shows that it is mainly caused by the relatively weak level of urbanization and financial development.

Table 5: The results of the regression test in the region

North region		Central region		South region	
Dig	0.487	Dig	0.701	Dig	0.532
	0.001		0.002		0.006
	***		***		***
Fin	0.484	Fin	-0.201	Fin	-0.254
	0.002		0.007		0.032
	***		***		**
Urb	0.045	Urb	0.273	Urb	0.194
	0.019		0.058		0.061
	**		*		*
Edu	-0.194	Edu	-0.478	Edu	-0.306
	0.037		0.014		0.031
	*		**		**
Gov	0.087	Gov	0.361	Gov	0.232
	0.045		0.069		0.065
	**		*		*
R^2	0.582	R^2	0.431	R^2	0.594
N	52	N	33	N	50

V. Conclusion

The digital economy has become a key driving force for the transformation of regional economic structure. Through factor analysis and orthogonal least squares regression, it is confirmed that the digital economy has a significant positive impact on regional economic structure, with a regression coefficient as high as 0.446, indicating that for every unit increase in the level of development of the digital economy, the proportion of the tertiary industry in the GDP will increase by 0.446 percentage points. This result fully verifies the theoretical hypothesis that digital economy promotes the advanced economic structure through the mechanisms of technological innovation, resource optimization and allocation, industrial integration and upgrading, and spatial effect release.

The analysis of regional heterogeneity reveals that the digital economy plays the most significant role in the central region, with an impact coefficient of 0.701, much higher than that of 0.532 in the southern region and 0.487 in the northern region, and this difference mainly stems from the central region's better digital infrastructure, higher innovation capacity and talent concentration effect, which enables digital technology to be more fully applied to the transformation and upgrading of traditional industries. The level of financial development and urbanization also have a positive contribution to the transformation of economic structure, with regression coefficients of 0.286 and 0.205 respectively, reflecting the positive contribution of financial support and urbanization to the optimization of industrial structure.

It is worth noting that the level of education investment shows a negative correlation with the transformation of economic structure, with a coefficient of -0.273, suggesting that the training of talents in each region should be more closely aligned with the market demand, to avoid the disconnection between the training of talents and industrial demand. In the future, regions should formulate differentiated digital economy development strategies according to their own characteristics, focus on strengthening digital infrastructure construction, promoting the in-depth integration of digital technology and traditional industries, accelerating the cultivation of digital talents in line with market demand, and promoting the transformation and upgrading of regional economic structure to a higher level.

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