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An Empirical Study on the Impact of Machine Learning-based Information Resource Management System on Regional Economic Development Patterns

Yuchen Jin[1,✉], Yining Chen[1], Yetong Huo[1]

[1] *International School of Hebei University, Baoding, Hebei, 071000, China*

ABSTRACT

The construction of information resource management system is a promotion for upgrading industrial structure and enhancing independent innovation capability. Based on the city-level data of a region from 2010 to 2022, the evaluation index system of information resource management system and regional economic development mode is established, and the variables are measured according to the collected data using gray correlation analysis method. Then double machine learning method is applied to explore the influence effect of information resource management system on regional economic development model. The baseline regression analysis reveals that the information resource management system can promote the regional economic development model, with a regression coefficient of 0.029, and the conclusion still holds after the stability test. The heterogeneity results show that regions with better economic foundation (0.067) and peripheral cities (0.036) are more significantly affected by the positive spillover effect of the information resource management system. This paper combines machine learning algorithms with traditional causal inference to explore the role path of information resource management system to promote regional economic development model, which provides empirical evidence and decision-making reference for promoting regional economic development.

Keywords: dual machine learning, gray correlation analysis, benchmark regression analysis, evaluation index system, regional economic development model

1. Introduction

Information Resource Management System (IRMS) is an important information management tool designed to analyze, classify, statistic and monitor all kinds of information assets quantitatively and qualitatively so that the information resources can be maximally utilized and managed to improve the informationization operation efficiency and management level [1-4]. It can help organizations

✉ Corresponding author.
E-mail address: 19031420639@163.com (Y. Jin).
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achieve comprehensive management and utilization of information resources and improve the availability and accessibility of information resources. With the continuous development of information technology, information resource management system has gradually become an indispensable part of various industries [5-8]. It can help organizations better manage and utilize information resources, improve work efficiency and decision-making, and have an important impact on the regional economic development model [9-11].

A regional economic development model is a model for the development of a particular type of economy in an economic system in which a region adopts policies and steps based on the characteristics of its resources [12-13]. This model focuses on the overall requirements of achieving regional economic growth, improving people's livelihoods and achieving social harmony, and aims to effectively manage and optimize the development and use of regional resources, improve the structure of the regional economy, adjust the investment structure in line with the level and characteristics of regional development, and promote the coordinated development of the regional economy [14-17]. There are various types of regional economic development models, including technological innovation, marketization, public service and comprehensive development [18-19].

The study takes the information resource management system as the core explanatory variable and the regional economic development model as the explanatory variable, selects the evaluation indexes of the two variables respectively, and measures them by combining the gray correlation analysis method. The data of 60 cities in a region from 2010 to 2022 are selected as the research samples and analyzed based on the dual machine learning method. The correlation analysis of the model is used to initially discuss the relationship between the information resource management system and the regional economic development model, and then the benchmark regression analysis is utilized to reveal the effect of the role between the two and to validate the research hypotheses made. Subsequently, the heterogeneity analysis is carried out to discuss the impact effects of the information resource management system in cities with different economic development bases as well as in the center/surrounding cities, and the stability test is conducted. In conjunction with the empirical analysis, strategies for the promotion of regional economic development patterns by information resource management systems are explored.

2. Research hypothesis

Through the construction of a unified resource information exchange and sharing system, the information resource management system can effectively enhance the decision-making efficiency of the governmental decision-making level in all aspects of urban management and emergency response, open up the correlation channels between events, and reduce the cost of single and comprehensive decision-making. At the same time, information resource management can drive the investment of social capital, promote the value-added development and innovation of information resources in society, so as to fully explore and utilize the value of data, drive social innovation and entrepreneurship, and promote social and economic development. Based on this, this paper proposes research hypotheses:

H1: The information resource management system has a facilitating effect on the regional economic development model.

H2: The impact of information resource management system on the regional economic development model and the mechanism of its action may vary due to the differences in economic base and urban areas.

3. Empirical design

The purpose of this paper is to test the effect of the information resource management system on the regional economic development model based on the machine learning method. Because the regional economic development model has rich connotations and is often influenced by many factors in the economy and society, it is necessary to control as much as possible the interference of other factors on urban economic growth in the model setting. The high-dimensional control variables will produce regularization bias in the estimation process, affecting the accuracy of the regression results. To mitigate the robustness of traditional causal estimation methods, a dual machine learning model is used for the evaluation.

3.1. Selection of variables

1) Explained variable: regional economic development model (REDM). Based on the literature and theoretical knowledge to determine the seven dimensions of regional economic development, which are industrial structure, investment, consumption, foreign trade and import and export, resources, labor force, and people's living standards, and after that, select the explanatory variables from these seven dimensions to construct the economic indicator system of the explanatory variables. The indicator system of regional economic development model is shown in Table 1. Based on this evaluation index system, this paper uses gray correlation analysis to measure the regional economic development model.

Table 1. Index system of regional economic development model

Index	Specific variable
Industrial structure	The annual output of the first production
	The annual output of the second production industry
	The annual output of the third industry
Invest	The whole club will invest in fixed assets
	Actual direct investment in foreign capital
Consumption	Total retail sales of consumer goods
	Government expenditure
Import and export	Customs import value
	Customs export value
Resources	Energy production
	Financial institution deposit balance
	Percentage of education expenditure
	Scientific achievement level
Labor force	Year-end population
	Year-end employment staff
People's living standards	The per capita disposable income of urban residents

2) Core explanatory variables: information resource management system (IRMS). When establishing the evaluation index system of information resource management level, it is necessary to consider factors such as personnel quality, infrastructure construction, input funding, etc., and at the same time, combine with the actual situation of regional development, so as to form an index system that can systematically describe the level of regional information resource management. The evaluation index system of information resource management level is shown in Table 2, and the indicators take into account the application status of information resource management, infrastructure, human resources, efficiency index, and inputs in information security. Similarly, the regional information resource management level is evaluated by gray correlation analysis based on the constructed indicator system.

Table 2. The index system of information resource management level

Index	Specification
The ratio of information investment to fixed assets	It reflects the investment of informationization, including software, hardware, network, informationization human resources and other investment.
Computer ownership per 100 people	Including large, medium, small machines, servers, workstations, micromachines, etc.
Computer network rate	The proportion of computers connected to the Intranet of the enterprise.
Coverage of information technology in information collection	The application of policy regulations, market, production, sales, technology, management and human resource information collection.
Information talent index	The number of employees of the information related professionals above bachelor's degree.
The cost of information security accounts for the proportion of all information investment	The cost of information security includes software, hardware, training, and human resources expenditure.
Application rate of information safety measures	The application of information backup, prevention of illegal intrusion, prevention of disease, information, safety system and safety awareness culture.
The ratio of information funding to growth	Annual growth ratio of information special funds

3) Control variables. Since the dual machine learning model will not be affected by high-dimensional control variables, in order to improve the precision and accuracy of the model estimation, this paper controls the factors affecting the inclusive development of urban economy as much as possible. The control variables selected in this paper include: 1) urbanization level (urban), expressed using the ratio of regional urban resident population to regional resident population. 2) The level of openness to the outside world (open), expressed as the ratio of the actual amount of foreign direct investment to the gross regional product. 3) The level of financial expenditure on people's livelihoods (medical), expressed using the ratio of medical expenditure to general public budget expenditure. 4) Degree of government intervention (fiscal), which is expressed using the share of fiscal expenditures in regional GDP. 5) Educational resources (edu), expressed using the total number of elementary, middle, high school, and post-secondary schools divided by the total population of the area. In addition, considering the possible nonlinear relationship between the variables, this paper further adds the quadratic terms of the above economic variables to the regression for model fitting, as well as city fixed effects and time fixed effects to control for differences in the individual and time dimensions of the city.

3.2. Data sources

This paper constructs panel data at the level of 60 prefectural cities in a region from 2010 to 2022, with variables sourced from the China Statistical Yearbook, the China Regional Economic Statistical Yearbook, and the statistical bulletin on the national economic and social development of each prefectural city.

3.3. Methods of analysis

3.3.1. Machine learning problems. Data-based machine learning is an important aspect of modern intelligence technology, the essence of which is to find statistical patterns from observing the data itself and to make predictions about future data. Specifically, the machine learner problem is to estimate the dependencies of the inputs and outputs of a system from a given set of training samples by some means of training, and it is hoped that this estimation will result in as accurate an output prediction as possible for any given input.

where system S is the learning object which gets a certain output y for a certain input x and LM is the desired learning machine with output $y^{'}$ for input x.
The machine learning problem can be expressed in general terms as an unknown dependency between variables $y^{'}$ and x, i.e., following some unknown joint probability $F(x,y)$ and the aim of machine learning is to find an optimal function $f(x,\omega^{'})$ among a set of functions $\{f(x,\omega)\}$ based on a sample of n independent and identically distributed observations $\{(x_1,y_1),(x_2,y_2),\cdots,(x_n,y_n)\}$ that makes the expected expected risk:

$$R(\omega)=\int L(y,f(x,\omega))dF(x,y) \tag{1}$$

Min. Where $f(x,\omega)$ is called the set of prediction functions, $\omega\in\Omega$ is the generalized parameter of the function, and $L(y,f(x,\omega))$ is the loss due to the prediction of y with $f(x,\omega)$. Prediction functions are also called learning functions, learning models or learning machines.

After obtaining a predictive function $f(x,\omega)$, for a new input x, the x corresponding output y is introduced based on $f(x,\omega)$. This is called generalization and it is the ultimate goal of machine learning.

3.3.2. Dual machine learning models. The dual machine learning model used in this paper:

$$Y=g_0(D,X)+U \tag{2}$$

$$D=m_0(X)+V \tag{3}$$

where Y is the explanatory variable, D is the explanatory variable, $D\in\{0,1\}$, X are covariates, $g_0(\cdot)$ and $m_0(\cdot)$ are functions of unknown form, and U and V are errors.

Treatment Effect Estimation and Hypothesis Testing:

The underlying assumption of the model is $E(U\mid X,D)=0, E(V\mid X)=0$.

Since D it is not additive and divisible, this model takes into account the general heterogeneity of the treatment effects, so the treatment effect θ_0 is the average treatment effect (ATE) in this model:

$$\theta_0=E[g_0(1,X)-g_0(0,X)] \tag{4}$$

and the participant average treatment effect (ATET):

$$\theta_0=E[g_0(1,X)-g_0(0,X)\mid D=1] \tag{5}$$

The covariate X affects the treatment variables D, $m_0(X)=E\left(D\mid X\right)$ through the propensity score, and the explanatory variable Y can be obtained through the function $g_0(D,X)$, which are unknown but can be obtained by machine learning methods.

Let $Y=D\theta_0+f_0(X)+U, l_0(X)=E(Y\mid X)$ be obtained:

$$l_0(X)=m_0(X)\theta_0+f_0(x) \tag{6}$$

Further available:

$$Y-l_0(X)=V\theta_0+U \tag{7}$$

Therefore, in order to estimate the treatment effect θ_0, Equation $Y-l_0(X)=Y-E(Y\mid X)$ and Equation $V=D-m_0(X)=D-E(D\mid X)$ will need to be applied, and machine learning methods such as bagging, neural networks, random forests, and boosting can all be used to learn the expectation functions $E(Y\mid X)$ and $E(D\mid X)$, from which θ_0 can be estimated.

In this paper, two-fold cross-validation will be utilized to improve the stability of the model and the reliability of the prediction, so the full sample data will be divided into the following two sub-samples: l and I^c. The dual machine learning method applied in this paper is divided into the following three steps:

In the first step, the functional form of $E(Y \mid X)$ is learned on a subset of l, based on which the residual $\hat{u}_{Y|X}$ is obtained on I^c.

The second step is to learn the functional form of $E(D \mid X)$ on subset l, based on which residual $\hat{u}_{D|X}$ is obtained on I^c.

In the third step, subsets l and I^c are interchanged and the above two steps are repeated to do a regression on the residuals, and the resulting slope coefficient is the estimate of treatment effect θ_0.

3.3.3. Gray correlation analysis. Gray correlation analysis is a branch of gray system theory. The application of gray correlation analysis is a widely accepted method for the comprehensive evaluation of things and phenomena affected by multiple factors from a holistic viewpoint. The steps of comprehensive evaluation using gray correlation analysis are:

1) Determine the evaluation index system according to the purpose of evaluation. Collect evaluation data. Set n data series to form the following matrix:

$$(X_1^{'}, X_2^{'}, \cdots, X_n^{'}) = \begin{bmatrix} x_1^{'}(1) & x_2^{'}(1) & \cdots & x_n^{'}(1) \\ x_1^{'}(2) & x_2^{'}(2) & \cdots & x_n^{'}(2) \\ \cdots & \cdots & \cdots & \cdots \\ x_1^{'}(m) & x_2^{'}(m) & \cdots & x_n^{'}(m) \end{bmatrix} \tag{8}$$

2) Establish a reference series with the maximum value of each indicator and standardize the raw data, i.e., divide each indicator value by the maximum value of that indicator respectively.

3) Calculate, one by one, the absolute difference between the indicator sequence (comparison sequence) and the corresponding element of the reference sequence for each evaluated object. That is:

$$| x_0(k) - x_i(k) | \; K = 1, 2, \cdots, n; i = 1, 2, \cdots, n \tag{9}$$

n is the number of subjects to be evaluated.

4) Determine $\min\limits_{i=1}^{n} \min\limits_{k=1}^{n} | x_0(k) - x_i(k) |$ and $\min\limits_{i=1}^{n} \min\limits_{k=1}^{n} | x_0(k) - x_i(k) |$.

5) Calculate the association coefficient. From the following formula, the association coefficient of each comparison sequence with the corresponding element of the reference sequence is calculated separately:

$$\zeta_i(k) = \frac{\min\limits_i \left| x_0^{'}(k) - x_i^{'}(k) \right| + \rho \cdot \max\limits_i \left| x_0^{'}(k) - x_i^{'}(k) \right|}{\left| x_0^{'}(k) - x_i^{'}(k) \right| + \rho \cdot \max\limits_i \left| x_0^{'}(k) - x_i^{'}(k) \right|} \tag{10}$$
$$K = 1, 2, \cdots, m$$

where: ρ is the discrimination coefficient, in (0, 1) take the value, if ρ is smaller, the correlation coefficient between the difference between the larger, the stronger the ability to distinguish. Usually ρ takes 0.5.

6) Calculate the association order. For each evaluation object (comparison sequence), calculate the mean value of the association coefficient between its indicators and the corresponding elements of the reference sequence, in order to reflect the association relationship between each evaluation object and the reference sequence, and call it the association sequence, notated as:

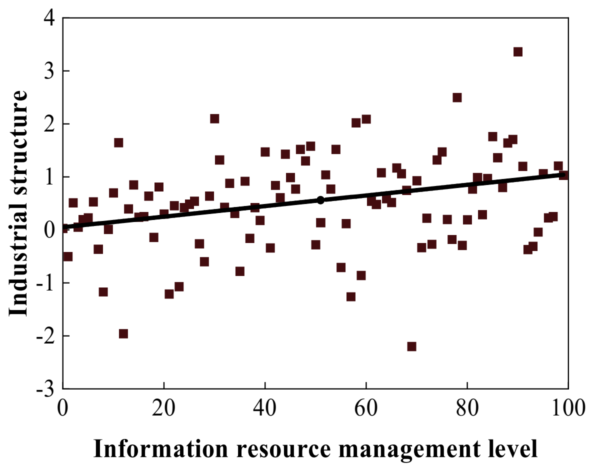
$$r_{0i} = \frac{1}{m} \sum_{k=1}^{m} \zeta_i(k) \tag{11}$$

7) Comprehensive evaluation results based on the correlation order of each observation object.

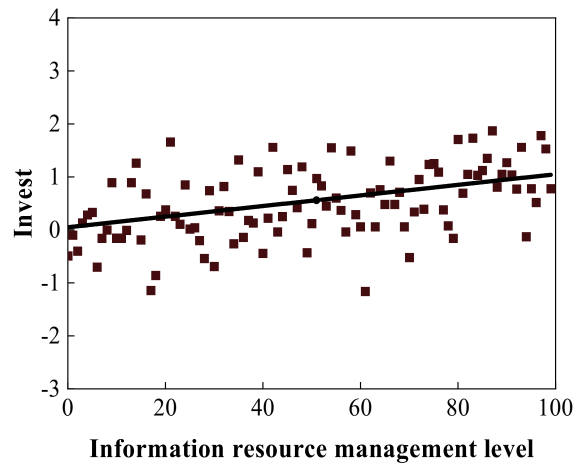
4. Analysis of empirical results

4.1. Correlation analysis

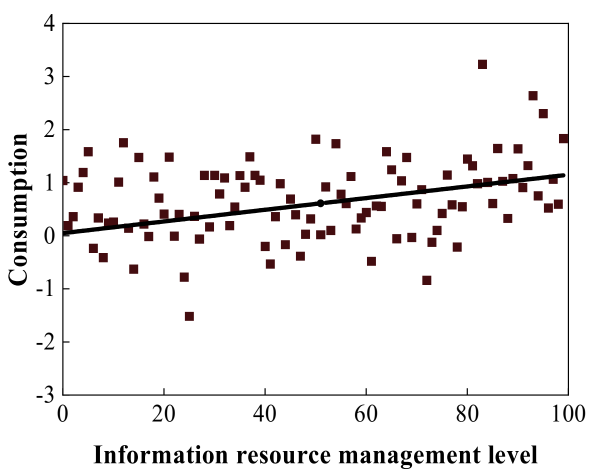
Based on the data collected, the correlation between the dimensions of the information resource management system and the regional economic development model was analyzed. The correlation between information resource management system and regional economic development model is shown in Figure 1. Figures (a) to (g) show the corresponding changes in industrial structure, investment, consumption, foreign trade and import/export, resources, labor force, and people's living standard in the sample region's information resource management system and the regional economic development model of the place from 2010 to 2023. All dimensions in the information resource management system and the regional economic development model show a clear negative correlation, indicating that regional economic development is also relatively better in regions with higher levels of information resource management. Since the above relationship does not control for the influence of other factors, it needs to be further confirmed by empirical regression.



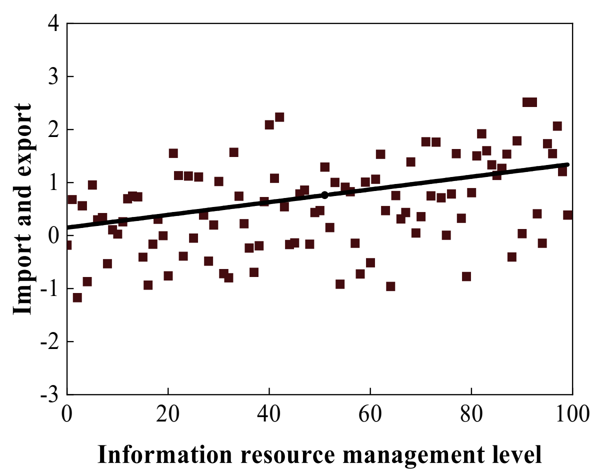
(a)Industrial structure



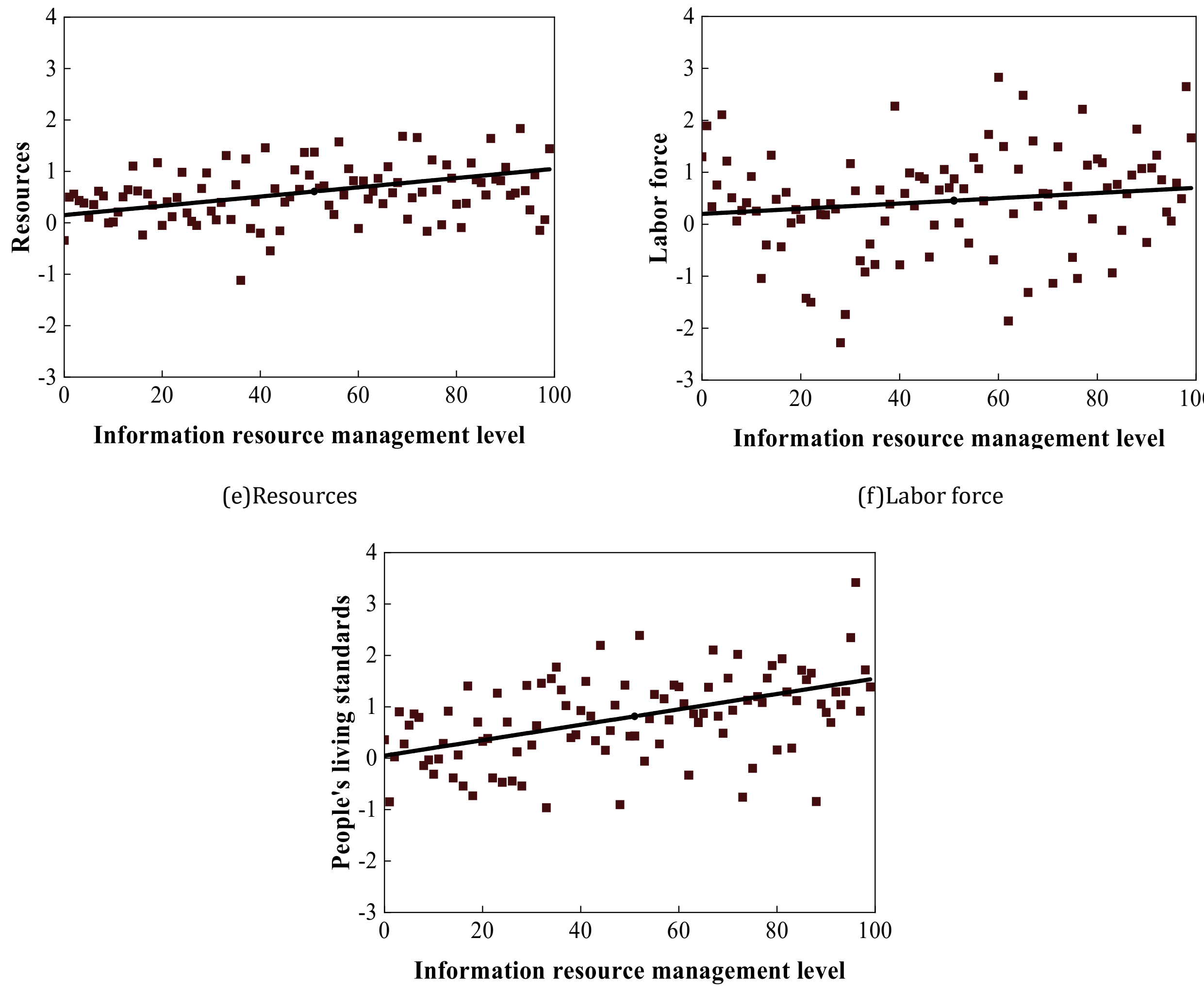
(b)Invest



(c)Consumption



(d)Import and export



(e)Resources

(f)Labor force

(g)People's living standards

Fig. 1. The correlation analysis results

4.2. Analysis of baseline regression results

In order to reduce the estimation bias caused by the overfitting of the machine learning algorithm, the sample segmentation was carried out according to the ratio of 1:3 in the estimation process, and the gradient propulsion algorithm was used to predict and solve the main regression and auxiliary regression, and the benchmark regression results are shown in Table 3, the ***, ** and * represent significant at the level of 1%, 5% and 10%, respectively, and the robust standard error of heteroskedasticity in parentheses is in parentheses.

Column (1) controls for year fixed effects, city fixed effects, and city economic variables, and the regression results show that the regression coefficient of the core explanatory variable IRMS is significantly positive at the 1% level. This means that IRMS can promote the development of regional economic development patterns, and for every 10 percentage points increase in the level of IRMS, the level of economic development patterns will increase by 0.34 percentage points on average. The information resource management system not only becomes a new driving force and engine of economic growth, but also provides more development opportunities for economic entities in different regions, and comprehensively improves the regional economic development mode.

Considering that it takes some time for the information resource management system to be fully utilized from implementation to promotion and then to energy efficiency, the explanatory variables are treated as lagged one period. The estimated coefficient of the test result in Column (2) is still significantly positive (0.029), but the promotion effect of the information resource management system on the regional economic development model in the lagged period is weakened compared with the current period effect.

In addition, to ameliorate the effect of potential endogeneity on the estimation results, the dual machine learning model in the main regression is replaced from a partially linear model to an instrumental variable model in column (3). The regression coefficient of the core explanatory variable, IRMS, remains significantly positive (0.227), indicating that the information resource management system indeed promotes the regional economic development model. So far, the research hypothesis H1 is verified.

Table 3. The results of the benchmark regression

Variable	(1)	(2)	(3)
IRMS	0.034***	0.029*	0.227**
	0.054	0.038	0.265
Primary term of control variable	Control	Control	Control
Quadratic term of control variable	Control	Control	Control
Year fixed effect	Control	Control	Control
Urban fixation effect	Control	Control	Control
Sample size	683	683	683

4.3. Heterogeneity analysis

The sample is divided into cities with better economic development foundation and cities with weaker economic development foundation for testing. At the same time, in order to investigate whether the enhancement effect of the information resource management system on the regional economic development model will strengthen the "center-periphery" imbalance structure, the sample is divided into center and peripheral cities for group regression.

The regression results of the heterogeneity analysis are shown in Table 4. Compared with regions with a weaker foundation for economic development, the absolute value of the regression coefficients of the disposition variables of the sample in regions with a better foundation for economic development is larger (through the test of coefficient difference between groups), with the regression coefficients of 0.035 and 0.067, respectively, and they are more significant in statistical significance. This is mainly due to the fact that cities with a better foundation for economic development tend to have a more diversified digital service ecosystem and more abundant financial support, and are able to integrate information resources in a more in-depth and comprehensive manner and develop and utilize them. At the same time, although regions with a better economic base are more sensitive to the regional economic development effects of IMS, IMS also provide unique development opportunities for cities with a weaker economic base.

In the group classified as central cities, although the regression coefficient value of the core explanatory variable IRMS is larger (0.073), it is not statistically significant, while the regression coefficient value of the core explanatory variable IRMS in the group of peripheral cities is significantly positive at the 5% level. This not only implies that IRMS has a more obvious effect on the enhancement of regional economic development in peripheral cities, but also indicates that IRMS accelerates the flow of technology and capital to peripheral cities that are relatively resource-poor, narrowing the development gap with the center city while enhancing the economic efficiency of the peripheral cities, and effectively mitigating the regional imbalance of the industrial layout. In summary, research hypothesis H2 is established.

Table 4. Heterogeneity analysis regression results

Variable	Foundation of economic development		Centre - peripheral cities	
	High	Low	Centre	Peripheral
IRMS	0.067***	0.035**	0.073	0.036**
	0.056	0.038	0.051	0.049
Control variable	Control	Control	Control	Control
Year fixed effect	Control	Control	Control	Control
Urban fixation effect	Control	Control	Control	Control
Sample size	683	683	683	683

4.4. Stability tests

In this paper, the robustness test is conducted in three aspects: changing the time scale and replacing the core explanatory variables. The results of the robustness test are shown in Table 5. First, to mitigate the lag effect of the impact of the information resource management system, this paper focuses the monthly data to the annual level for regression analysis. This is done by taking the average of each variable of the monthly data in each year to generate the annual data, and it is found that the improvement of the level of information resource management is still able to effectively enhance the regional economic development. As in columns (1) and (2), on average, a 10 percentage point increase in the level of information resource management is associated with an average 0.42 increase in regional economic development per year.

The regression results in columns (2) and (3) show that the coefficients of the information resource management system are positive and significant at the 1% level with and without control variables, indicating that the information resource management system enhances regional economic development significantly. Specifically, for every 10 percentage point increase in the level of information resource management, regional economic development increases by 0.37. This is comparable to the magnitude of the marginal effect estimated in the benchmark regression and suggests that the estimates in this paper are relatively robust.

Table 5. Results of robustness test

	(1)	(2)	(3)
IRMS	0.042***		
	0.188		
IRMS		0.060***	0.037***
		0.202	0.026
Constant	0.495***	0.193***	0.455***
	0.592	0.294	0.175
Control variable	YES	NO	YES
Year fixed effect	Control	Control	Control
Urban fixation effect	Control	Control	Control
Sample size	683	683	683
R^2	0.156	0.287	0.585

4.5. Strategic Analysis

Combined with the empirical analysis above, the strategies of information resource management for regional economic development are discussed.

4.5.1. Improved quality and effectiveness of information resources. Improve the quality and effectiveness of information resources to better serve regional economic development. Information resource management applies system management methods, through policies and regulations and other means, to comprehensively regulate and control the elements of information resource management, focusing on quality, highlighting priorities, coordinating development, realizing optimal configuration, and strengthening the construction of information resources. Coordinating the relationship between information resource management and the social environment, as well as between the elements of the information resource management system, improving the quality and effectiveness of information resources as well as informatization, and enhancing the potential of information resource management can prevent and avoid information crises, thus realizing overall benefits.

4.5.2. Creation of advanced smart tools. The creation of advanced intelligent tools through information technology provides material guarantees for regional economic development. The technical management of information resources is to engage in the collection, organization, storage and dissemination of information resources by technical means so as to develop and utilize them more effectively. Through information technology, it promotes the creation of advanced intelligent tools, raises the level of material and energy exploitation and utilization, develops new resources, improves the traditional industrial structure, promotes the creation of new industries, improves social efficiency and reduces environmental pollution, thereby realizing the goal of regional economic development.

4.5.3. Strengthening information resource management. With the deepening of informatization, the social information environment is becoming more and more complex and changeable, and the number of information problems is increasing, such as information flooding, information pollution, information barriers, information crime, information alienation and information conflicts. Strengthening the management of information resources, controlling the direction of information flow, developing information management from manual mode to automation, networking and digitization, and realizing all-round collection, high-rate processing, high-density storage and long-distance transmission of information, enable people to comprehensively, quickly and accurately find the information they need, so as to better develop and utilize the information resources, and lay a good foundation for the development of the regional economy. The information resources can be better developed and utilized, thus laying a good foundation for regional economic development.

5. Conclusion

This paper constructs the evaluation index system of information resource management system and regional economic development model, and uses gray correlation analysis to assess both. Taking the panel data of a region from 2010 to 2022 as an example, the role of information resource management system on the regional economic development model is examined by using the dual machine learning method. The results show that the information resource management system has a significant positive effect on the regional economic development model at the 1% level, and the regression coefficient of the lagged period is 0.029, which indicates that for every 1 percentage point increase in the level of information resource management, the regional economic development improves by 0.029 percentage points, which verifies the facilitating effect of the information resource management system on the regional economic development model, and this conclusion, after the robustness test still holds. The regression coefficients of the information resource management system in the cities with better and weaker economic base development are 0.067 and 0.035 respectively, i.e. the influence effect of learning resource management on regional economic development is more obvious in the areas with better economic base. The regression coefficients of the explanatory variables of the center and peripheral cities are 0.073 and 0.036, respectively, and the information resource management system presents a significant effect only in the peripheral cities ($p < 0.05$). The development of the information age promotes the transformation of the economic development mode, in this regard, the quality and efficiency of information resources should be improved, advanced intelligent tools should be created through information technology, information resource management should be strengthened, information crisis should be prevented, and regional economic development should be guaranteed.

About the Authors

Yuchen Jin was born in Cangzhou, Hebei, China, in 2004. He is currently an undergraduate student at Hebei University in China. He currently studying at School of international, Hebei University. His main research direction is Information management and information system.

Yining Chen was born in Baoding, Hebei, China, in 2004. She is currently an undergraduate student at Hebei University in China. She currently studying at School of international, Hebei University. Her main research direction is Information management and information system.

Yetong Huo was born in Baoding, Hebei, China, in 2004. She is currently an undergraduate student at Hebei University in China. She currently studying at School of international, Hebei University. Her main research direction is international economics and trade.

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