



Research on Evaluation of Innovation Performance of Traditional Industries Empowered by Digital Intelligence Based on Fuzzy Information

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SUMMARY: *Science and technology input and output efficiencies have been a very important consideration in evaluating the innovativeness and evolution of traditional industries. In this research, the spatio-temporal trends of digital intelligence innovation performance in traditional industries during the provincial level in China between 2013 and 2022 are examined using the DEA-Malmquist index. Because of the existence of missing or ambiguous evaluation criteria, the paper presents a hybrid of fuzzy information granulation and support vector machine regression (FIG-SVM model) to address the voids in data. As it is shown by the results, the FIG-SVM model is successfully used to deal with fuzzy data and improves the assessment of the performance of innovation in traditional industries. In terms of time analysis, average values of total factor productivity, technical efficiency, and technological progress of the last decade are 0.969, 0.998, and 0.975 respectively, which indicates that there is great potential in improving the digital intelligence-based innovation in traditional industries. The geographical distribution of the performance of digital intelligence innovation in traditional industries depicts a trend of being stronger in the east, medium in the west, and weaker in the central regions.*

KEYWORDS: *DEA-Malmquist index; fuzzy information granularity algorithm; support vector machine regression; industrial innovation performance; spatial and temporal evolution trend*

1 Introduction

Innovation has always been a powerful driving force for industrial development, and the level of innovation capacity has become a decisive factor for whether a region or even a country can achieve competitive advantage [1]. In terms of the drivers of economic growth and prosperity, innovation capacity has become a key factor in national or regional economic growth, while traditional resources such as national power and influence have gradually taken a back seat [2]. Since the development of the first industrial revolution in the 1860s, innovation has been the goal that countries around the world have been constantly pursuing, and the strength of innovation ability directly affects the scientific and technological status of a country or region in the world. Traditional industries, as the pillar industries of national economic growth, play an extremely important role in this dynamic uncertain and highly competitive digital intelligence environment [3].

The innovation and development of traditional industries is a process of comprehensive influence of various factors, industrial innovation does not only refer to technological innovation, but should be expanded to product innovation, management innovation, market

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innovation, institutional innovation, etc. [4]. Industrial innovation is a “systematic project”, which requires the integration of all aspects of innovation resources. How to break through the bottleneck of the original industry through the systematic coordination of technology, products, management, market and other aspects of traditional industries, and how to utilize new production factors to combine, upgrade, innovate, and create industries is the key to industrial innovation [5, 6]. It is especially important to adjust industrial structure and improve the international competitiveness of traditional industries by analyzing the influencing subjects and influencing factors of industrial innovation performance and constructing an evaluation model applicable to evaluating industrial innovation performance on this basis [7, 8]. In this context, the development of fuzzy set theory provides new ideas and methods for solving performance evaluation problems [9]. Compared with traditional methods, fuzzy set theory has many advantages in describing uncertainty and portraying ambiguity, and it can reflect as much information as possible that wants to be expressed, and it is now widely used in different socio-economic fields, such as risk assessment, site selection decision-making, and project evaluation [10, 11]. The research on enterprise evaluation based on fuzzy set theory has made some progress, which is used to provide theoretical support and methodological guidance for industrial innovation performance evaluation.

The literature on the subject has focused more on finding out what influences the enterprise innovation performance, and researchers have done a lot of research in this field. Literature [12] emphasized the relevance of big data analytics in developing corporate strategies, which show that the innovation performance of the Jordanian banking sector is positively moderated by big data capabilities by investigating the role of intellectual capital in innovation. Literature [13] used data envelopment analysis to assess the innovativeness of the traditional textile manufacturing industry, which involved assessing the capability of the firm to convert resources and commercialize the industrial property rights. The paper revealed that cluster organization had a quantifiable impact on the innovation performance of traditional businesses. Literature [14] created a semiparametric model based on panel data to explore the determinants of changes in innovation performance across various high-tech industries, revealing that the amount of money spent on R&D, number of people employed in R&D, and government subsidies play a significant role in the performance of enterprise innovation. Literature [15] analyzed the relationship between innovation management and performance in various industries around the world with structural equation modeling to determine the effect of knowledge management and innovation organization on innovation performance. It was shown that although the soft and hard management of knowledge did not have a significant impact on innovation performance, innovation organization had a significant positive impact. Literature [16] reported that tolerance to regional differences boosts innovation performance by attracting talents and lowering the barriers to the face-to-face interactions that facilitate knowledge exchange especially when there are high agglomeration economies. Literature [17] surveyed small and medium-sized enterprises to collect data and then analyzed the factors that influence innovation performance using Mplus and SPSS software. The paper concluded that management innovation is a strong contributor to innovation performance with the width of knowledge search being a mediator.

There are many methods for innovation performance evaluation, mainly including fuzzy comprehensive evaluation method, entropy weight TOPSIS method, data envelopment analysis method, etc. The Literature [18] has applied an advanced fuzzy hierarchical analysis approach to a holistic assessment of the school-enterprise cooperation innovation performance. The research created an assessment model that includes three main indicators and 22 sub-indicators, which showed that it had drawbacks including the slow pace of conversion of science and technology results. The results have given a picture of how innovation performance can be improved and optimized in this context. Literature [19], in order to solve the complexity and

opposite problems faced by the traditional enterprise innovation potential assessment, developed a real-time, comprehensive and integrated assessment method, and formulated the constituent indexes that best reflect the innovation potential of the enterprise by calculating the utilization rate and relevance of the innovation potential. Literature [20] analyzed data on the innovation performance of agricultural enterprises, extracting key innovation performance features through processes of data handling, transformation, and analysis. The assessment of innovation performance in these agricultural enterprises was then conducted using a GA-BP neural network model. Literature [21] examined the technological innovation capabilities and efficiency of enterprises across various scales, incorporating the cost of technological innovation into the efficiency index. This comprehensive assessment aimed to support the state's strategic allocation of technological resources to foster enterprise innovation and development.

Moreover, fuzzy knowledge has become popular in the assessment of corporate performance, which can be considered as a traditional multi-attribute decision problem using fuzzy data. Literature [22] discussed the role of triangular fuzzy information in assessing enterprise performance and formulated a multi-attribute decision-making model based on the triangular fuzzy weighted Eisenberg Enromien operator. This approach was shown to be feasible by giving a practical example of enterprise performance evaluation. Literature [23] developed a framework of evaluating the progress of enterprise accounting informatization, using intuitionistic fuzzy sets and cross-entropy methods to calculate the indicator weights. The findings, relying on the weighted scores, gave scientifically correct assessments of the informatization of the enterprise, pointing out the directions of improvement. Literature [24] fully utilized two fundamental operators in the hesitant triangular fuzzy technique to measure two main operators of the hesitant triangular fuzzy technique to evaluate the supply chain collaboration performance of manufacturing companies, providing valuable lessons on supply chain management. The effectiveness of the method was shown by the case study. In terms of enterprise innovation evaluation, reference [25] has applied a multi-attribute decision-making framework that is based on a fuzzy hesitant information to assess technological innovation performance in small and micro enterprises. It focused on two evaluation factors, namely, authenticity and unbiasedness and put high weights on them to enhance their influence on the assessment of innovation performance. Using the concept of fuzzy elements literature [26] developed a system to assess agricultural technological innovation capabilities and integrated the entropy weight approach with gray correlation coefficient approach to form a model. The evaluation of this fuzzy-based innovation capability was tested on a publicly available dataset.

Literature [27], on the other hand, uses intuitionistic fuzzy numbers to assess the innovation atmosphere of enterprise organizations, and by constructing the corresponding assessment index system and scoring each index, the assessment effect of this method in the example is more comprehensive and scientific, and the study provides a more practical method for the assessment of the innovation atmosphere of enterprise organizations.

The research deals with traditional industries in China that were developed through digital intelligence during the period of 2013-2022 at the provincial level. It creates a rating mechanism to evaluate the innovation performance of these industries based on variables like R & D personnel and investment, technology market turnover and quantity of patents filed and granted. Since it is intrinsically fuzzy data, the prediction and filling in of missing data are made using a fuzzy information granularity algorithm supported by support vector machine regression which ensures correct support in the evaluation. Based on this, the DEA-Malmquist index is used to determine the innovation performance of digitally enabled traditional industries in terms of both time and space.

2 Evaluation model construction of innovation performance of traditional industries empowered by digital intelligence

2.1 Evaluation of industrial innovation performance based on DEA modeling

The Malmquist index, as a part of the DEA model, gives an objective assessment of dynamic technical efficiency change. The combined use of DEA and Malmquist index is applied in this research to evaluate the innovation performance of traditional industries in a way that is dynamic.

2.1.1 DEA model

DEA, or Data Envelopment Analysis, is a nonparametric estimation method in linear programming. It is an evaluation method with relative effectiveness based on input-output data, utilizing linear programming and convex analysis to help decision makers calculate techniques for evaluating the relative efficiency of the same type of decision making units (DMUs) with multiple inputs and multiple outputs, and has now been widely used in solving practical problems in a variety of industries. There are a variety of theoretical models for DEA, which are generally categorized into the DEA-BCC model and the DEA-CCR model, but they differ in the corresponding models as well as the efficiency they illustrate. CCR model, but the difference between them is that the corresponding models are different, as well as the efficiency illustrated is also different: DEA-CCR model is assumed to calculate and analyze the corresponding efficiency of the overall synthesis in a constant state of scale payoffs; DEA-BCC model assumes that the overall scale payoffs are variable, and the synthesis efficiency is divided into purely technical efficiency and scale efficiency on the basis of the results of calculation and analysis of the CCR model. It is used to analyze the extent to which technical failures are responsible for the non-effective state of the decision-making unit.

First assume that there are j decision-making units (DMUs) in the model and that each of them has m types of input factors and s types of output factors, and that the corresponding input vectors are $X_j = (x_{1j}, x_{2j}, \dots, x_{mj})^T$, and the output vector is $Y_j = (y_{1j}, y_{2j}, \dots, y_{sj})^T$ and where $X_j > 0, Y_j > 0$, and these j decision units, denoted by $DMU_j (j = 1, 2, \dots, n)$, are in convexity, conicity, and conicity, with respect to any of these decision units DMU_j , nullity and minimality axiomatic assumptions, whose formulas are shown below. The formulas are shown below:

$$\min \left[\theta - \varepsilon \left(\sum_{i=1}^m S_i^- + \sum_{i=1}^m S_i^+ \right) \right] \quad (1)$$

$$s.t \begin{cases} \sum_{j=1, j \neq j_0}^n \lambda_j X_{ij} + s_i^- = \theta x_0 \\ \sum_{j=1, j \neq j_0}^n \lambda_j Y_{ij} - s_i^+ = Y_0 \\ s_r^- \geq 0, s_r^+ \geq 0 \\ r_j \geq 0, j = 1, L, n \end{cases} \quad (2)$$

In the above equation: θ is the effective value of the evaluation decision unit; ε is the non-Archimedean infinitesimal; λ_i is the weight, $\lambda_i \geq 0, i = 1, 2, \dots, n$; X is the input indicator and Y is the output indicator; s_r^+ is the relaxation variable for the output deficit; s_r^- is the input surplus slack variable.

If $\theta = 1$ and $S^+ = S^- = 0$, the decision unit DEA is valid.

If, and $S^+ = S^- \neq 0$, then the decision unit is weakly DEA valid.

If $\theta < 1$, then the decision unit is DEA invalid.

2.1.2 Malmquist exponential modeling

Malmquist index is applied in DEA models to measure the degree of change in the dynamics of technical efficiency and to study the cause-and-effect relationship between the changes in the dynamics of technology and the change in the overall factor productivity. With the use of the Malmquist index model, it is feasible to review the development of efficiency of different decision-making units with respect to time, separating the variations in allocation of resources and improvements in technology.

In terms of output using technology T_t in period t , the Malmquist index can be expressed as:

$$M_0(x_{t+1}, y_{t+1}, x_t, y_t) = D_0^t(x_{t+1}, y_{t+1}) / D_0^t(x_t, y_t) \quad (3)$$

Likewise, when examining the Malmquist index from an output-oriented approach, considering technology T_{t+1} during time period $t+1$, the expression can be demonstrated through this equation:

$$M_0^{t+1}(x_{t+1}, y_{t+1}, x_t, y_t) = D_0^{t+1}(x_{t+1}, y_{t+1}) / D_0^{t+1}(x_t, y_t) \quad (4)$$

To remove the instability due to the arbitrary choice of a time interval, the geometric mean is used on the two given statements and it gives this form, which is the Malmquist index that expresses the change in productivity between subsequent periods. In particular::

$$M_0(x_t, y_t, x_{t+1}, y_{t+1}) = \left[\frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \times \frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_t, y_t)} \right]^{1/2} \quad (5)$$

In this formulation, D_0 represents the distance function while M_0 signifies the Malmquist index. A value of M_0 below unity indicates declining total factor productivity between period t and period $t+1$; $M_0 > 1$ equaling unity signifies stable total factor productivity across period t through period $t+1$; values of M_0 exceeding unity demonstrate rising

Drawing from extensive scholarly literature, the previously described Malmquist index may be reconfigured as shown below, breaking down productivity variation into dual elements: technical efficiency alongside frontier productivity shifts:

$$\begin{aligned} M_0(y_{t+1}, x_{t+1}, y_t, x_t) &= \frac{D_0^{t+1}(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \times \left[\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_{t+1}, y_{t+1}C)} \times \frac{D_0^t(x_t, y_t)}{D_0^{t+1}(x_t, y_t)} \right]^{1/2} \\ &= EC \times TP \end{aligned} \quad (6)$$

TP stands here as the technical progress index and EC means the technical efficiency change index. Technical efficiency change index can be further divided into a scale efficiency index (SC) and the pure technical efficiency index (PC):

$$M_0(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^t(x_t, y_t)} \left[\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_0^t(x_t, y_t)}{D_0^{t+1}(x_t, y_t)} \right]^{1/2} \quad (7)$$

The technical efficiency change component of the Malmquist Index can then be further subdivided into scale efficiency changes and pure efficiency changes:

$$M_0(x_t, y_t, x_{t+1}, y_{t+1}) = \frac{S_0^t(x_t, y_t)}{S_0^t(x_{t+1}, y_{t+1})} \times \frac{D_0^t(x_{t+1}, y_{t+1} / VRS)}{D_0^t(x_t, y_t / VRS)} \times \left[\frac{D_0^t(x_{t+1}, y_{t+1})}{D_0^{t+1}(x_{t+1}, y_{t+1})} \times \frac{D_0^t(x_t, y_t)}{D_0^{t+1}(x_t, y_t)} \right]^{1/2} \quad (8)$$

In this formulation, the first component captures the variation in scale efficiency, the second component is a mirror of pure technical efficiency variation and the third component is an indicator of technical changes.

2.2 Construction of the evaluation index system and data sources

2.2.1 Selection of evaluation indicators

This paper follows the guidelines of comprehensiveness, scientific rigor, comparability and practicality in developing the evaluation index system. One-year time lag is used and certain indicators based on other researches are adapted. The evaluation indicators are organized and rearranged to develop a system of evaluation of empowerment of digital intelligence. The system will concentrate on input indicators, which include R&D personnel and funding, and output indicators, which include technology market turnover and the amount of patent applications granted. These form the backbone of the conventional industry innovation performance assessment framework.

2.2.2 Data sources

The DEA is not a parametric technique but rather a non-parametric approach that combines mathematical, economic and management methods to estimate the technical efficiency of homogeneous decision-making units. In this research, the 31 provinces, municipalities, and autonomous regions in China will be chosen as the evaluation units to achieve homogeneity. The input-output data of these areas are analyzed during the period of 2013-22 to evaluate the innovation performance of the digitally enabled traditional industries. The main sources of primary data include China Science and Technology Statistics yearbook, China Torch Statistics yearbook and EPS database. Missing data in some years are interpolated using the FIG-SVM model.

2.3 Data processing methods

Because the input and output indicators data are somewhat fuzzy in some years, which restricts the ability to effectively assess the innovation performance of traditional industries that have been enabled by digital intelligence, this section presents a support vector machine regression

model based on fuzzy information granularity to predict and fill the gaps in missing data. Below is the detailed approach.

2.3.1 Model of the model information granulation algorithm

The fuzzy data clusters are the clusters of data that can be expressed as fuzzy sets and are formed with respect to the functional similarity, features, or actions of the objects. Density or sparsity of these granules depends wholly on the boundaries set to the information cluster. The idea of the algorithm is to reduce the complexity of problem solving by fuzzy granulation of time series by means of fuzzy sets. The process consists of 2 steps, i.e., the windowing step and the fuzzification step: windowing is to partition the given data series into subdatasets, each of which serves as an operation window; fuzzification is to fuzzy each window of division to generate sub-fuzzy sets. The core of fuzzy information granularization is to window the original data sequence X and build a reasonable fuzzy set on each window subset, so that it can ignore irrelevant details on a data interval, and at the same time can reasonably represent the original data. The specific procedure is to build a fuzzy particle p on a given data sequence X as well as an argument G such that:

$$p = x \text{ is } G \tag{9}$$

Its essence is the process of determining a function $p = A(x)$. $A(x)$ describes the degree of affiliation of the variable x belonging to the fuzzy domain G . Commonly used fuzzy particles are triangular fuzzy particles, Gaussian fuzzy particles and parabolic fuzzy particles. According to the characteristics of the thrust calibration slope data, the triangular fuzzy particle is selected in this paper, and its affiliation function $A(x)$ is shown in equation (10):

$$A(x) = \begin{cases} 0 & x < a \\ \frac{x-a}{m-a} & a \leq x \leq m \\ \frac{b-x}{b-m} & m < x \leq b \\ 0 & x > b \end{cases} \tag{10}$$

where: x is the input time series; a, m and b are the parameters, for a single fuzzy particle, a describes the minimum value of the variation of the corresponding original data, m describes the average level of the variation of the corresponding original data, and b describes the maximum value of the variation of the corresponding original data.

2.3.2 Support Vector Machine Regression Prediction Algorithm Modeling

Support vector regression (SVR) is a supervised learning method based on the idea of the VC dimension of statistics and structural risk minimization (SRM). It is distinguished by the use of a kernel function, which converts a nonlinear problem in the attribute space of the original sample to a linear programming problem in a high-dimensional feature space. The underlying algorithm is based on the following principle:

Given a sample of data $\{x_i, y_i\}_{i=1}^k, x_i \in R^d, y_i \in R$, SVR simplifies the regression problem by introducing an insensitive loss function ξ , hence the algorithm is also known as ξ -SVR. The linear model in mapping space the estimation function is:

$$y = f(x) = (\omega, \varphi(x)) + b \quad \varphi: R^d \rightarrow G, \omega \in G \quad (11)$$

where b is the bias. In optimizing the estimation function, extreme values are taken for the optimization objective:

$$\min J = \frac{1}{2} \|\omega\|^2 + C \sum_{i=1}^k (\xi_i^* + \xi_i) \quad (12)$$

Make:

$$\begin{cases} y_i - (\omega, \varphi(x_i)) - b \leq \varepsilon + \xi_i \\ (\omega, \varphi(x_i)) + b - y_i \leq \varepsilon + \xi_i^* \\ \xi_i, \xi_i^* \geq 0, (i = 1, 2, \dots, k) \end{cases} \quad (13)$$

where: C serves as the penalty parameter, employed for balancing empirical risk against confidence risk; higher C values enhance data-fitting capability. Parameters ξ_i and ξ_i^* function as relaxation parameters, managing the linear non-separability constraints. Parameter ε governs the regression approximation deviation along with the model's generalization capacity; larger ε values reduce support vector quantity while simultaneously diminishing accuracy. During practical implementation, the dual formulation of equations (12) and (13) receives frequent application for deriving:

$$\begin{aligned} W(\alpha, \alpha^*) &= -\frac{1}{2} \sum_{ij=1}^k (\alpha_i - \alpha_i^*)(\alpha_j - \alpha_j^*) \\ &(\varphi(x_i), \varphi(x_j)) + \sum_{ij=1}^k (\alpha_i - \alpha_i^*)(y_i - \varepsilon) \end{aligned} \quad (14)$$

The constraints are:

$$\begin{cases} \omega = \sum_{i=1}^k (\alpha_i - \alpha_i^*) x_i \\ 0 \leq \alpha_i, \alpha_i^* \leq C \\ \sum_{i=1}^k (\alpha_i - \alpha_i^*) = 0 \end{cases} \quad (15)$$

Then the regression estimation function can be expressed as:

$$f(x) = \sum_{i=1}^k (\alpha_i - \alpha_i^*) (\varphi(x_i), \varphi(x)) + b \quad (16)$$

$$f(x) = \sum_{i=1}^k (\alpha_i - \alpha_i^*) K(x_i, x) + b \quad (17)$$

The kernel function $K(x_i, x) = (\varphi(x_i), \varphi(x))$. For a given nonlinear time series

$\{x_1, x_2, \dots, x_t\}$, the mapping $f : R^m \rightarrow R$ can be built to satisfy using the known historical data of x_t to predict x_{t+1} :

$$\hat{x}_{t+1} = f(x_t, x_{t-1}, \dots, x_{t-(m-1)}) \tag{18}$$

2.3.3 FIG-SVM model prediction process

The innovation performance data of traditional industries empowered by digital intelligence, with one year as the length of the window division, after using the triangular fuzzy function to fuzzy granularity of the sample data, the SVR is used to fit the regression to the fuzzy granularity of the time series data, and the prediction model applicable to the relevant indicators is trained. The flow of the prediction model based on FIG-SVR is shown in Figure 1, and the specific steps are as follows:

- 1) The selection of factors influencing the innovation performance of traditional industries empowered by digital intelligence (input and output indicators) and the organization of data samples.
- 2) Data sample window division, the author adopts one year as the standard of window division, then the length of the window is the length of the original data sample divided by the year.
- 3) Selection of triangular fuzzy affiliation function on the window time series sample data for information fuzzification.
- 4) Calculate to get the window time series sample data after fuzzy information granulation processing.
- 5) The optimal kernel function parameters g and penalty factor C are obtained by grid search crossover and genetic algorithm validation of optimization.
- 6) Train to get the optimal SVR fitting regression prediction function.
- 7) Determine the prediction value and verify the prediction effect.

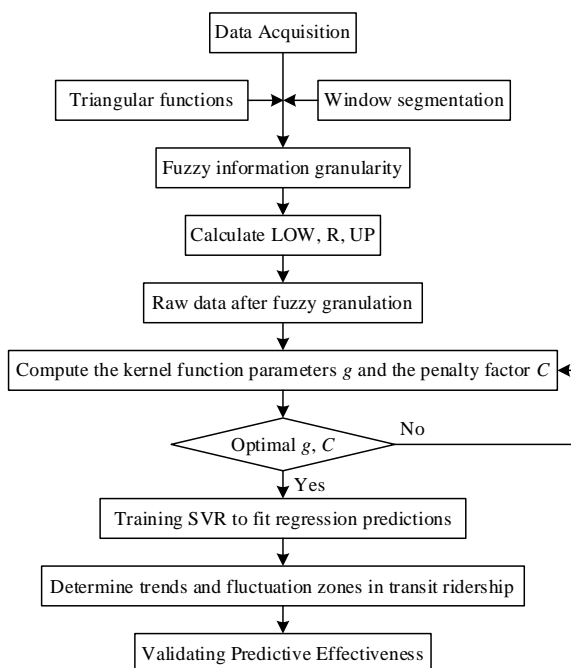


Figure 1: FIG-SVR model prediction process

3 Empirical analysis

3.1 Forecast results of industrial innovation performance indicators

3.1.1 Granularization of fuzzy information

This paper uses triangular fuzzy particles to granulate the fuzzy information on input and output data in the DEA model. The size of the granulation window is defined as 2 and the total number of windows is 14. The variables Low, R and Up represent the three parameters of the fuzzification function of the fuzzy particles, i.e., a , m and b that are the minimum, average and maximum values of the data changes with respect to each fuzzy particle. The granulation results of the original data in fuzzy form are shown in Fig. 2. The figures (a) and (b) are the input of R&D personnel and R&D funding respectively with the significant change in the granulation window at the window 6.

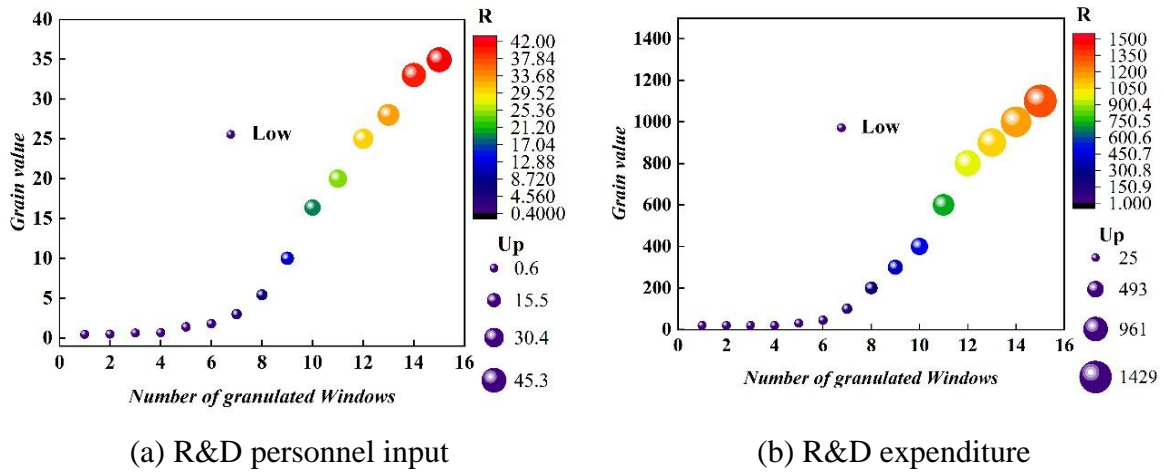


Figure 2: The results of the original data are fuzzy grained

3.1.2 SVR Parameter Optimization Processing

The choice of kernel function parameters significantly influences the generalization performance of the support vector machine (SVR), making the optimization of these parameters a crucial step. In this study, we apply both the K-fold cross-validation method and the genetic algorithm to optimize the penalty parameter c and the Gaussian kernel parameter g , comparing the results from these two methods to determine the best values for c and g . This combined approach offers better parameter selection compared to using a single optimization method, thereby enhancing the model's prediction accuracy.

(1) K-fold Cross-Validation Method. The K-fold cross-validation technique is used to optimize the parameters Low, R, and Up after the granulation of R&D personnel input, R&D funding input, technology market turnover, and the number of patent applications granted. The optimization is performed using Matlab R2018a, where the function `SVMcgForRegress` is employed to fine-tune the parameters c and g . As an example, the lowest value of the granulated data for R&D personnel input is used, and the SVM model optimization is carried out through K-fold cross-validation. The results of the parameter selection process using K-fold cross-validation are shown in Fig. 3.

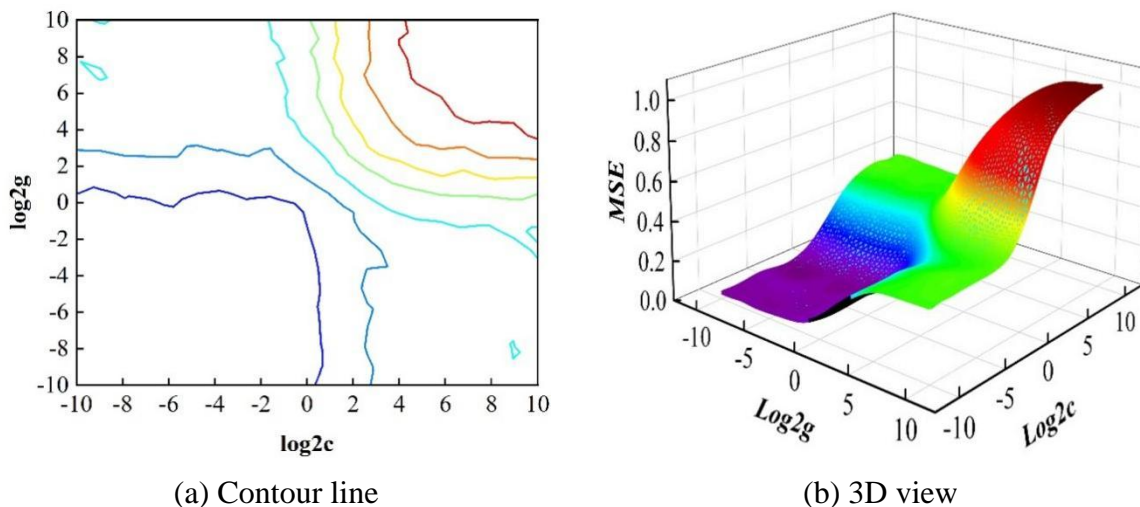


Figure 3: The choice results of the k folding cross-validation parameter

(2) Genetic Algorithm. The genetic algorithm is used to optimize the parameters Low, R, and Up after the granulation of R&D personnel input, R&D funding input, technology market turnover, and the number of patent applications approved. The function `gaSVMcgForRegress` is implemented with Matlab R2018a to optimize the penalty parameter `ccc` and the Gaussian kernel parameter `ggg`. To illustrate, the minimum value (Low) of the granulated fuzzy data on R&D personnel input is chosen as an example and the SVM model is optimized using the genetic algorithm. Figure 4 shows how to optimize the parameter.

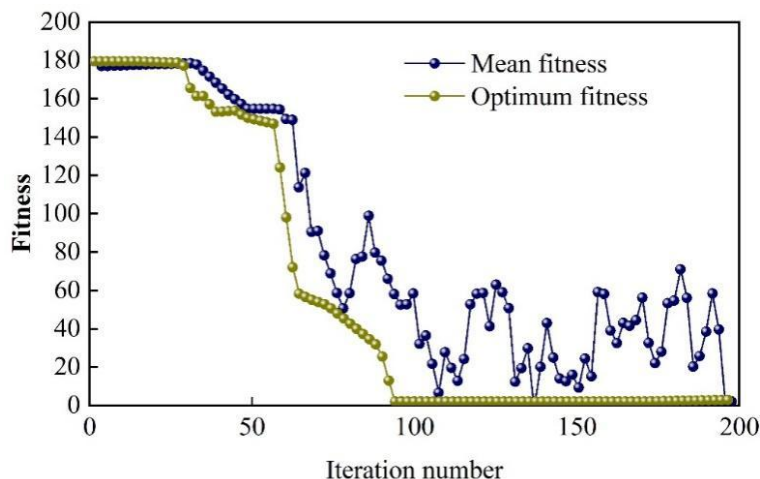


Figure 4: Parametric optimization process

Comparison of Fitting Results obtained through Optimization Algorithms. After the granulation of fuzzy information on every indicator the K-fold cross-validation approach and the genetic algorithm were used to optimize the parameters Low, R, and Up. These two methods were compared based on their fitting results to determine the predicted values that have the best fitting performance. In the case of the minimum of the granulated fuzzy data of R&D personnel input (Low) the K-fold cross-validation method yielded the SVR machine parameter `c` and `g` of 722.058 and 0.014925 respectively. The genetic algorithm gave the parameters as 78.6592 and 0.023815. Comparing both optimization methods using the mean square error and correlation coefficient, the optimal values of `ccc` and `ggg` were identified. The optimization results are

compared in detail in Table 1.

By comparing them, it is shown that even though the correlation coefficients of the two approaches are comparable, the mean square error of the K-fold cross-validation approach is somewhat less compared to the genetic algorithm. Consequently, in the case of the parameter Low of the R&D personnel input fuzzy information granularity, the K-fold cross-validation method can be considered as a more desirable option of optimizing parameters. The mean square error of this method is also relatively small and the correlation coefficient is quite near to 1 which means that the prediction curve fits much better.

Table 1: The optimization algorithm is compared

Algorithm	MSE	R ²
K cross check	0.215988	0.995788
Genetic algorithm	0.225467	0.995951

3.1.3 SVR-based regression prediction of granulation data

The K-fold cross-validation method was used in training the support vector machine to predict regression using the R&D personnel input fuzzy information granularity as the parameter Low. Figure 5 illustrates the comparison between the original data and the predicted regression data. Most of the predicted values are very close to the original data except some outliers. It means that the prediction model of the support vector machine developed according to the K-fold cross-validation method is highly accurate. Therefore, choosing a suitable optimization approach can be very useful in improving the accuracy of the regression predictions.

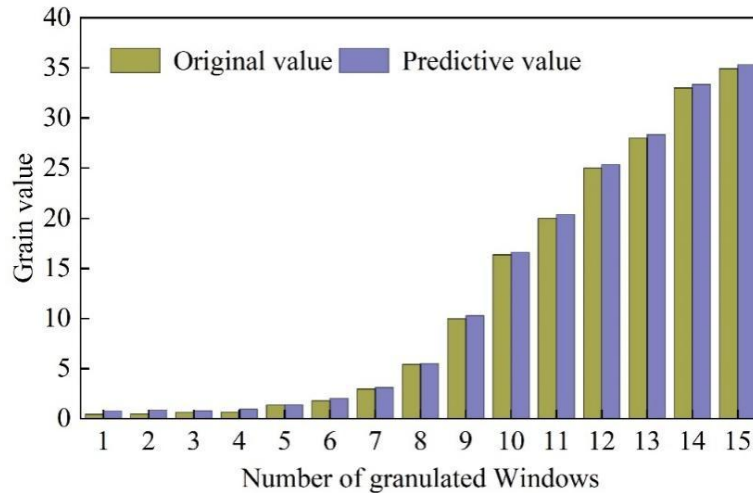


Figure 5: The original data was compared with the regression prediction data

The best penalty parameter c and kernel function parameter g were applied in training the support vector regression (SVR) model that subsequently produced predicted figures of different measures of innovation performance in the digitally enabled traditional industry in the years 2017 and 2018. The exact data can be found within Table 2. The estimated average values of R&D personnel input, R&D funding input, technology market turnover and authorized patent applications are 397,855,000 people, 141.48 billion yuan, 4.95 billion yuan, and 245,188 respectively, which is quite similar to the real values. The predicted results derived through the FIG-SVR model will be utilized later on to compute the efficiencies.

Table 2: The prediction results of the innovative performance indicators

Year		R&D personnel input	R&D expenditure	Technical market turnover	Number of patent applications
2017~2018	Low	33.6248	1088.5	666522	225158
	R	39.7855	1414.8	4949385	245188
	Up	49.6732	15021.5	9218659	313299

3.2 Evaluation of Innovation Performance of Traditional Industries Empowered by Digital Intelligence

3.2.1 Dynamic evaluation of innovation performance in traditional industries

The Malmquist index effectively captures the dynamic changes and heterogeneity in total factor productivity across different provinces. In this study, DEAP2.1 software is employed to evaluate the innovation performance of digital intelligence-enabled traditional industries in China at the provincial level from 2013 to 2022. The time trend is displayed in Table 3, where Fffch, Techch, Pech, Sech, and FTP represent changes in technological efficiency, technological advancement, pure technological efficiency, scale efficiency, and total factor productivity, respectively. At the temporal level, the innovation performance characteristics of digital intelligence-enabled traditional industries in various provinces and cities over the past decade can be summarized as follows:

(1) The average total factor productivity over the past decade is 0.969, reflecting a decline of -3.1%, suggesting a general downward trend in the innovation performance of digital intelligence-empowered traditional industries. The fluctuations in total factor productivity over the past ten years are significant, highlighting the substantial uncertainty in innovation performance. Furthermore, except for the years 2017 and 2022, total factor productivity grew, while it declined to varying degrees in other years.

(2) The mean technical efficiency is 0.998, showing a minimal decrease of -0.2%, which is the smallest reduction compared to total factor productivity and technological progress. Although the decline in technical efficiency is the least, the overall change is still considerable, indicating the need for further improvement in the technical efficiency of digital intelligence-enabled traditional industries. Comparing this with the change in technical progress, we observe growth in 2016, 2017, 2019, and 2022, while technical efficiency declined in these years to varying extents. This suggests a lag in the adaptation of technical efficiency to technological advancements, which may have contributed to the stagnation in improving total factor productivity.

(3) The mean value of technical progress is 0.975, reflecting a decrease of -2.5%, indicating that there is considerable potential for improving the technological progress of traditional industries empowered by digital intelligence. The technical progress change is the most drastic fluctuation among the 3 efficiency trends, reflecting the urgency and complexity in terms of technical progress enhancement. On the one hand, technological progress is an important support to enhance the adaptability and reliability of emergency technology and equipment, and the sharp fluctuations indicate that its supporting role still needs to be enhanced. On the other hand, the sharp fluctuations also show the complexity of the factors affecting technological progress.

Table 3: The innovation performance time trend of traditional industrial industries

Start and end years	Effch	Techch	Pech	Sech	TFP
2013-2014	0.993	0.904	0.997	0.998	0.898
2014-2015	1	0.993	0.997	1.005	0.993
2015-2016	0.931	1.059	0.934	0.999	0.983
2016-2017	0.995	1.094	0.995	1	1.085
2017-2018	0.988	0.905	0.974	1.018	0.893
2018-2019	0.993	1.008	1.009	0.987	0.997
2019-2020	1.008	0.893	0.995	1.014	0.896
2020-2021	1.075	0.905	1.087	0.992	0.970
2021-2022	0.997	1.011	1.005	0.995	1.006
Mean	0.998	0.975	0.999	1.001	0.969

Table 4 shows the results of the spatial change in innovation performance of digital intelligence-enabled traditional industries by province over the past 10 years. The spatial change pattern is summarized here in three aspects:

In the last ten years, the only places that have reached total factor productivity above 1 are Beijing, Yunnan, Shanghai, and Qinghai, with growth rates of 11.1%, 2.1%, 1.8, and 0.4, respectively. Conversely, the total factor productivity in the rest of the 27 provinces has fallen to different levels. In a regional context, the eastern region performed better than the western and central regions, indicating that industrial innovation was highest in the east during the last 10 years, followed by the central and western regions.

(2) There were 17 provinces that reported technical efficiencies of 1 or higher, and 14 provinces with technical efficiencies less than 1. The trend is consistent with the lesser decline in the average technical efficiency, however variations across time imply that it is necessary to enhance technical efficiency in these industries even more.

(3) Except Beijing, Shanghai, Xinjiang, and Hainan, where the technical progress was more than 1, the rest of the 27 provinces recorded different levels of reduction in technical progress. It means that the technological development of traditional industries in these provinces has a lot of space to improve.

Table 4: Traditional industrial innovation performance space situation

Area	Effch	Techch	Pech	Sech	TFP
Beijing	1.029	1.055	1.026	1.006	1.111
Tianjin	1.010	0.992	1.009	1.004	0.999
Hebei	0.971	0.936	0.972	1	0.906
Shanxi	0.997	0.961	0.999	0.998	0.959
Inner Mongolia	0.947	0.983	0.947	0.998	0.928
Liaoning	0.958	0.998	0.961	1	0.958
Jilin	0.993	0.952	1	0.993	0.942
Heilongjiang	0.991	0.962	0.988	1.004	0.949
Shanghai	1	1.018	1	1	1.018
Jiangsu	1	0.964	1	1	0.964
Zhejiang	1	0.982	1	1	0.982
Anhui	1.006	0.964	1.007	1	0.967
Fujian	1.005	0.947	1	1.005	0.948
Jiangxi	1	0.954	1	1	0.954
Shandong	0.987	0.941	0.998	0.991	0.925
Henan	0.989	0.963	0.989	1	0.949
Hupei	1.014	0.969	1.008	1.008	0.981
Hunan	0.999	0.973	1	0.998	0.972
Guangdong	1	0.989	1	1	0.989
Guangxi	0.978	0.964	0.979	0.998	0.941
Hainan	0.989	1.005	1	0.989	0.992
Chongqing	1.018	0.948	1.05	0.989	0.962
Sichuan	0.982	0.958	0.983	0.997	0.938
Guizhou	0.988	0.962	0.987	1.004	0.948
Yunnan	1.031	0.993	1.035	0.998	1.021
Tibet	1	0.974	1	1	0.974
Shaanxi	1	0.959	1	1	0.961
Kansu	1.054	0.939	1.055	0.998	0.987
Qinghai	1.015	0.992	1.012	1.009	1.004
Ningxia	1.009	0.928	0.992	1.021	0.934
Xinjiang	0.968	1.017	0.984	0.987	0.981
Mean	0.998	0.972	0.999	1.000	0.969

3.2.2 Static evaluation of key time points

In order to resolve the critical time periods that can be associated with total factor productivity growth in the dynamic analysis, the indicators of input and output of the innovation performance of digital intelligence-based traditional industries in China at the provincial level in 2017 and 2022 are further evaluated at a static level. Table 5 shows the results.

On average, the values of comprehensive efficiency in 2017 and 2022 are 0.828 and 0.857 respectively. The mean value of pure technological efficiency is 0.843 in 2017 and 0.879 in 2022, and that of scale efficiency is 0.983 and 0.977 respectively. In comparison with 2017, the overall technological efficiency and pure technological efficiency have increased in 2022, but the scale effect has reduced slightly.

Table 5: The difference between the innovation performance of important time node industry

Area	2017				2022			
	Overall efficiency	Technical feedback	Scale merit	Return of scale	Overall efficiency	Technical feedback	Scale merit	Return of scale
Beijing	1	1	1	Invariant	1	1	1	Invariant
Tianjin	0.654	0.662	0.993	Diminishing	1	1	1	Invariant
Hebei	0.976	0.980	0.999	Increasing	0.749	0.750	0.998	Increasing
Shanxi	1	1	1	Invariant	0.985	0.995	0.994	Increasing
Nei Monggol	0.618	0.617	1	Invariant	0.490	0.504	0.977	Increasing
Liaoning	0.709	0.751	0.948	Diminishing	0.676	0.676	0.998	Invariant
Jilin	1	1	1	Invariant	0.918	1	0.918	Diminishing
Heilongjiang	0.578	0.578	0.998	Invariant	0.548	0.551	0.997	Increasing
Shanghai	1	1	1	Invariant	1	1	1	Invariant
Jiangsu	1	1	1	Invariant	1	1	1	Invariant
Zhejiang	0.995	0.999	0.998	Increasing	1	1	1	Invariant
Anhui	0.653	0.672	0.975	Diminishing	0.734	0.736	0.996	Increasing
Fujian	0.671	0.681	0.997	Increasing	1	1	1	Invariant
Jiangxi	1	1	1	Invariant	1	1	1	Invariant
Shandong	1	1	1	Invariant	0.869	0.979	0.891	Diminishing
Henan	1	1	1	Invariant	0.882	0.883	0.998	Diminishing
Hubei	0.654	0.767	0.856	Diminishing	0.630	0.631	1	Invariant
Hunan	0.927	0.967	0.963	Diminishing	0.994	1	0.994	Diminishing
Guangdong	1	1	1	Invariant	1	1	1	Invariant
Guangxi	1	1	1	Invariant	0.799	0.807	0.994	Increasing
Hainan	0.798	0.814	0.984	Diminishing	0.886	1	0.886	Diminishing
Chongqing	0.855	0.876	0.980	Diminishing	0.912	0.960	0.954	Diminishing
Sichuan	0.779	0.830	0.942	Diminishing	0.826	0.841	0.988	Diminishing
Guizhou	1	1	1	Invariant	0.682	0.692	0.991	Increasing
Yunnan	0.411	0.413	0.997	Diminishing	0.962	1	0.962	Diminishing
Xizang	1	1	1	Invariant	1	1	1	Invariant
Shaanxi	1	1	1	Invariant	1	1	1	Invariant
Gansu	0.642	0.651	0.988	Increasing	0.809	0.823	0.988	Increasing
Qinghai	0.729	0.730	1	Invariant	0.795	0.873	0.914	Increasing
Ningxia	0.421	0.443	0.955	Increasing	0.691	0.716	0.968	Diminishing
Xinjiang	0.617	0.694	0.889	Diminishing	0.728	0.842	0.868	Diminishing
Mean	0.828	0.843	0.983		0.857	0.879	0.977	

4 Conclusion

The present paper combines fuzzy information granularity along with support vector regression (SVR) and DEA-Malmquist approaches to dynamically evaluate the total factor productivity of the traditional industries that are digitally intelligent-based in all provinces of China between 2013 and 2022. Also, DEA-BCC model is used to perform a static analysis of significant time points when total factor productivity increase takes place, which helps determine the spatial and temporal distribution patterns and tendencies of industrial innovation performance.

Using the FIG-SVR model, the predicted average values for R&D personnel input, R&D funding input, technology market turnover, and the number of patents applied and authorized closely align with the actual values, demonstrating its ability to effectively address fuzzy data

and accurately evaluate the innovation performance of digitally empowered traditional industries.

From a temporal perspective, the average total factor productivity over the last decade is 0.969, reflecting a 3.1% decrease, indicating a general downward trend in the innovation performance of digital intelligence-enabled traditional industries. The average values for technical efficiency and technological progress are 0.998 and 0.975, respectively, suggesting substantial room for improvement in technological progress within these industries. Spatially, the overall performance of digital intelligence in fostering innovation in traditional industries follows a pattern of "strong in the east, moderate in the west, and relatively weak in the central region." Notably, Beijing, Yunnan, Shanghai, and Qinghai have experienced significant growth, with increases of 11.1%, 2.1%, 1.8%, and 0.4%, while the remaining 27 provinces have seen varying degrees of decline in total factor productivity.

Furthermore, an analysis of key time points reveals that the eastern region is more responsive to critical events, effectively capturing the "window period" created by these events and leveraging it as an opportunity to accelerate regional industrial development.

Looking ahead, it is crucial to focus on speeding up the replacement of outdated technologies in traditional industries, enhancing the adoption of new materials and processes by companies, and establishing platforms for collaboration between government, industry, academia, and research institutions. These efforts will serve as key measures for advancing technological progress and offer an opportunity for the leapfrog development of industry technology.

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