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The performance evaluation of global expansion strategies of Chinese law firms based on the improved back propagation prediction model

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Abstract

This study aims to enhance the scientific nature of performance management and the efficiency of strategic execution for Chinese law firms in global expansion. The study employs the balanced scorecard to establish a performance indicator system spanning seven dimensions. These dimensions include finance, customers, internal processes, learning and growth, industry scale and influence, local development foundation, and market potential, enabling systematic and diversified performance evaluation. Second, by combining trend decomposition and fluctuation modeling, the trend-seasonal (TS)-Back Propagation (BP) performance prediction model is implemented to enhance the predictive ability of the performance of law firms' global expansion strategies. Experimental results show that compared with the traditional BP model and other six mainstream prediction models, the TS-BP model exhibits higher prediction accuracy and stability in six evaluation indicators. The TS-BP model demonstrates excellent generalization ability and stability across different city levels. Especially in first-tier cities, the mean squared error of the TS-BP model is below 0.01, far superior to other models. Meanwhile, the error in third-tier cities is still controlled at a low level, verifying the model's practical value and adaptability. This study integrates strategic management with artificial intelligence technology to enhance law firms' performance prediction capabilities. The study seeks to provide crucial data support and decision-making references for law firms to formulate precise international development strategies, optimize resource allocation, and adjust business approaches.

Keywords: Law firm; Performance evaluation; Globalization; Back propagation algorithm; Balanced scorecard

Introduction

With the in-depth advancement of the "Belt and Road" initiative and the acceleration of transnational economic and trade exchanges, the demand for Chinese law firms to establish overseas branches and participate in overseas projects has increased markedly. However, compared with countries with mature legal systems such as Europe, the United States, Japan, and South Korea, Chinese law firms still face many bottlenecks in the process of internationalization [1]. At present, the internationalization level of China's professional legal talents is insufficient; compound lawyers are scarce with cross-cultural communication skills, proficiency in multiple languages, and mastery of international rules. These problems result in blind spots in the expansion team's judgment of the local market. The overseas networks among law firms are not yet sound, and partnerships and strategic alliances mostly rely on informal personal connections, making it difficult to form sustainable and systematic resource sharing. In addition, there are remarkable differences in laws and regulations among target countries, including compliance standards, business access thresholds, and professional ethics requirements, which are different from domestic practices. Law firms often need to invest a lot of preliminary research and compliance costs to gain a foothold in the local market [2,3]. Although strategic expansion requires the support of a performance management system, most domestic law firms still limit the performance evaluation of overseas branches to the level of "financial indicators + rough customer satisfaction". They lack systematic monitoring methods for multiple dimensions such as organizational learning, process optimization, brand influence, and regional development foundation [4]. In most service industries, intelligent prediction technologies such as machine learning and neural networks have been widely used in scenarios such as customer demand prediction, risk early warning, and resource allocation. However, in the legal service field, especially research on strategic performance prediction at the law firm level, it is still extremely limited [5,6]. The traditional Back Propagation Neural Network (BPNN) model performs well in industries such as finance and retail [7]. However, this model faces increased modeling difficulties due

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to the privacy of legal service data and the diversification of indicators.

To address this gap, this study comprehensively applies the balanced scorecard and artificial intelligence (AI) technology to construct a performance evaluation system, realizing systematic and multi-dimensional measurement of law firms' global expansion strategic performance. In addition, it combines the BP model with Trend-Seasonal (TS) to enhance the capture of performance change trends and predictive ability. Compared with traditional static evaluation methods, this study breaks through the limitations of single-algorithm prediction in terms of methodology, innovatively integrating time series modeling with deep learning networks. Meanwhile, it verifies the model's generalization performance and practical adaptability through samples of different city levels, providing more forward-looking and accurate decision support for Chinese law firms in establishing international development strategies.

Literature Review

Performance evaluation, as an important part of organizational management, has always been a focus of attention in academia and practice [8]. Traditional performance evaluation methods mostly focus on financial indicators, such as profit margin, cost control, and revenue growth. However, a single financial perspective is difficult to fully reflect an organization's comprehensive competitiveness and sustainable development capabilities [9,10]. The balanced scorecard theory proposed by Kaplan and Norton (1996) pioneered the expansion of performance evaluation to multiple dimensions such as learning and growth, customers, and internal processes. They emphasized the combination of financial and non-financial indicators, and promoted the systematic and scientific development of performance management systems [11]. Afshar and Shah (2025) stated that the balanced scorecard was widely applied in multiple fields such as the service industry, medical care, manufacturing, and public management, showing strong applicability and flexibility [12]. With the rise of big data and AI technologies, many scholars have attempted to apply algorithms such as the neural network, support vector machine (SVR), and random forest (RF) to performance evaluation and prediction, to improve the accuracy and dynamic response ability of evaluation [13]. Gao et al. (2023) adopted the entropy weight set pair analysis method to audit and evaluate the comprehensive cost-benefit performance of marine development projects, and used the BPNN model to verify the evaluation results [14]. Sun and Sui (2023) integrated the green economic efficiency and economic growth theory, setting indicators from multiple dimensions such as policy, finance, communication, and society. They evaluated China's agricultural green ecological efficiency from 2002 to 2021 using the Data Envelopment Analysis (DEA) model, and fitted and verified the DEA results through BPNN. The study found that China's agricultural green ecological efficiency increased by 11.78% during this period. Concurrently, the prediction trend of BPNN was highly consistent with the DEA results, verifying the accuracy and feasibility of the combined model. Their study provided an empirical case of integrated modeling of BP and DEA for multi-dimensional performance indicator evaluation. It also had methodological reference significance for performance prediction research in other fields, such as legal services [15]. Ma and Chu (2024) applied the nonlinear mapping ability and adaptability of BPNN to construct a scientific research performance evaluation model, thus verifying the accuracy and updatability of the model through sample training and fitting experiments. This indicated that the BP model had strong feasibility and practical value in performance evaluation [16].

To sum up, current research on performance evaluation has gradually transformed from the traditional financial orientation to a multi-dimensional and systematic one; it integrates various theories and methods such as balanced scorecard, DEA, and AI algorithms, greatly enriching evaluation means and application scenarios. Nevertheless, most studies still have certain limitations. On the one hand, some studies focus on a single industry or a single perspective, ignoring the dynamic changes and strategic synergy needs of organizations in the process of global development. On the other hand, existing evaluation systems are mostly based on static data, lacking the predictive ability to predict the time-series changes and trends of performance indicators; this makes it difficult to meet the requirements for forward-looking and adaptability in organizational management in highly uncertain environments. Especially in the legal service industry, the international expansion of law firms involves multiple dimensions such as talent, service process, customer, and finance. At the same time, their performance is affected by multiple factors, including regional development foundation, policy environment, and market potential. Therefore, a model integrating the balanced scorecard's multidimensional framework with BPNN's dynamic predictive capability is urgently needed. This model would enhance comprehensive performance evaluation and trend analysis for law firms, supporting their strategic planning and risk management with scientific evidence.

Research Model

Performance evaluation by the balanced scorecard

This study adopts the balanced scorecard method to construct the performance evaluation system for the global expansion of law firms. The balanced scorecard is a tool that decomposes an organization's strategic goals into multi-dimensional performance indicators [17]. It usually covers four traditional dimensions: internal processes, customers, finance, and learning and growth, and transforms strategies into measurable indicator systems through causal relationships [18]. In view of the global context of law firms, this study designs seven primary indicator dimensions and their subordinate secondary indicators on the basis of the four traditional dimensions. It combines with additional perspectives such as industry scale and influence, local development foundation, and market potential. The specific indicators are displayed in Figure 1 [19].

Primary indicators	Secondary indicators	Abridge
Finance	Team Source Contribution	TSC
Customer	Customer Satisfaction	CS
	Customer Complaint Number	CCN
Internal Process	Team Collaboration	TC
	Business Performance Assessment	BPA
	Public Culture Activities	PCA
Learning and Growth	Training Record	TR
	Papers and Publications	PAP
Industry Scale and Influence	Globalized Individuals	GI
	Institutional Size	IS
	High-Quality Law Firms	HQLF
	Global Legal Connections	GLC
Local Development Foundation	Local Economic Development	LED
	Population Size	PS
	Talent Reserve Pool	TRP
Market Potential	Service Sector Level	SSL

Figure 1: Performance evaluation indicator framework based on the balanced scorecard

In Figure 1, the financial dimension measures the business revenue-generating capacity of law firms through Team Source Contribution (TSC); the customer dimension reflects service quality and customer reputation by combining Customer Satisfaction (CS) and Customer Complaint Number (CCN); the internal process dimension measures organizational operation efficiency through Team Collaboration (TC), Business Performance Assessment (BPA), and Public Cultural Activities (PCA); the learning and growth dimension reflects employee growth and knowledge output through Training Record (TR) and Papers and Publications (PAP); the industry scale and influence dimension comprehensively evaluates the industry status and international network of law firms through Global Individuals (GI), Institutional Size (IS), High-Quality Law Firms (HQLF), and Global Legal Connections (GLC); the local development foundation dimension depicts the regional development environment through Local Economic Development (LED), Population Size (PS), and Talent Reserve Pool (TRP); finally, the market potential dimension measures the expansion potential of the local legal service market through Service Sector Level (SSL). This indicator system provides all-around and high-dimensional data support for the model.

Performance evaluation based on the improved BP model

To enhance the predictive ability for the global expansion performance of law firms, this study constructs a TS-BP prediction model that combines TS and BPNN. Time series analysis is a method for modeling and prediction based on the regularity of data changes over time. It effectively identifies long-term trends, cyclical fluctuations, and short-term disturbances by extracting trend, seasonal, and residual terms from the data [20-23]. In this study, time series analysis is first used to decompose the performance indicator data, thereby reducing noise interference in the data and making subsequent predictions more stable and accurate. This decomposition process helps reveal the inherent evolutionary structure of the data and provides clearer input signals for the neural network. BPNN is a typical feedforward artificial neural network, consisting of an input layer, one or more hidden layers, and an output layer. Its core feature is weight update through the error BP algorithm. Its advantage lies in its strong nonlinear fitting ability, which can learn potential rules from complex inputs and is suitable for multi-dimensional, nonlinear data modeling tasks [24-26]. This study employs BPNN to fit the data decomposed by time series. Through training to learn the complex changing relationships in performance data, it achieves high-precision prediction of future performance levels.

First, the historical performance data series is decomposed into trend, seasonality, and residual components. Then, the additive model is used to express the temporal decomposition, and the calculation is shown in Equation (1) [27]:

$$X_t=T_t+S_t+R_t \tag{1}$$

X_t represents the observations for period t; T_t stands for the trend component, S_t refers to the seasonal component, and R_t denotes the residual (stoch) component. The trend component T_t estimated by sliding average. For the case of season length m, the central moving average can be taken, expressed as follows [28]:

$$T_t=\frac{1}{m}\sum_{i=-k}^{k} X_{t+i} \tag{2}$$

$$m=2k+1 \tag{3}$$

X_{t+i} refers to the t+ith observation in the original time series data; i and k represent the offset index and the half width of the smoothing window.

After detrending, the seasonal component is calculated using the detrending value at the same time in each cycle, as follows [29,30]:

$$S_e=\frac{1}{N}\sum_{i=1}^{N}\left(X_{i\cdot m+e}-T_{i\cdot m+e}\right) \tag{4}$$

$$X_t'=X_t-S_t \tag{5}$$

e represents the eth moment in the season, N is the complete number of periods observed, and X_t' denotes the de-seasonalized data.

X_t' is normalized as the input of BPNN. The BPNN model adopts a single hidden layer structure to fit and predict the deseasoning sequence. The output is the performance prediction $\hat{y}$ at the future moment. Assuming that the hidden layer has n neurons, the calculation reads [31,32]:

$$h_j=g\left(\sum_i w_{ji} x_i+b_j\right),\quad j=1,\dots,n \tag{6}$$

$$\hat{y}=g\left(\sum_j v_j h_j+c\right) \tag{7}$$

x_i means the input; h_j denotes the output of the jth neuron in the hidden layer; w_{ji} and v_j refer to the weights from input to the hidden layer and from the hidden to the output layer, respectively; b_j and c are the corresponding biases; g stands for the activation function (such as the sigmoid function).

The model uses mean squared error (MSE) as the loss function, and the calculation is described as Equation (8):

$$E=\frac{1}{2}\sum_k\left(\hat{y}_k-y_k\right)^2 \tag{8}$$

y_k denotes the true value, and $\hat{y}_k$ represents the model output (predicted value).

The gradient of the loss function to the weight is calculated by the BP algorithm. The weights are updated using the gradient descent method, and the calculation is expressed as [33,34]:

$$w_{ji}^{(new)}=w_{ji}^{(old)}-\eta\frac{\partial E}{\partial w_{ji}} \tag{9}$$

$$v_j^{(new)}=v_j^{(old)}-\eta\frac{\partial E}{\partial v_j} \tag{10}$$

η refers to the learning rate. For the gradient of the weight v_j in output layers, it is calculated as follows:

$$\frac{\partial E}{\partial v_j}=(\hat{y}-y)\, g'(\cdot)\, h_j \tag{11}$$

During the network training process, continuous iterations are carried out until the loss converges or the maximum number of iterations is reached. After the training is completed, the final prediction can be obtained according to the predicted detrending value $\hat{X}_{t+1}'$ by adding the seasonal component. The calculation can be written as Equation (12):

$$\hat{X}_{t+1}=\hat{X}_{t+1}'+S_{t+1} \tag{12}$$

By combining the trend and seasonal components of time series with non-linear neural network prediction through the TS-BP model, the fitting ability for non-stationary series can be improved. The performance evaluation prediction process based on the TS-BP model is presented in Figure 2.

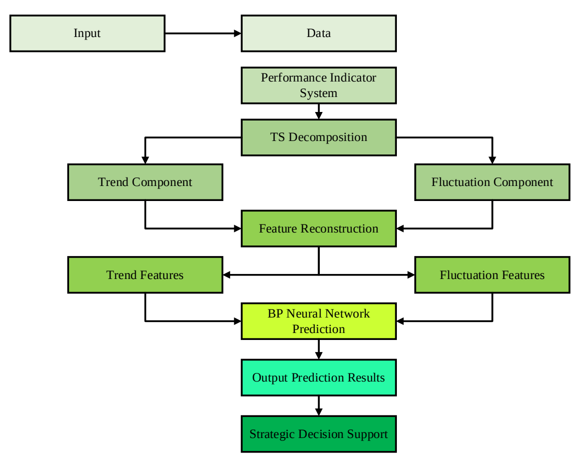


Figure 2: performance evaluation prediction process using the TS-BP model

Experimental Design and Performance Evaluation

Datasets collection

The data of this study is sourced from the China City Statistical Yearbook, Chambers China's list of high-level law firms and lawyers, the National Thousand Foreign-Related Lawyers Talent Pool, China Legal Service Network, and public data from local judicial administrative departments. This ensures the authority, timeliness, and representativeness of the data, which can systematically reflect the development foundation and global influence of law firms in various cities during their internationalization process. Among them, the China City Statistical Yearbook, sponsored by the National Bureau of Statistics, is a highly authoritative annual compilation of statistical data. It systematically collects core statistical data of major cities across the country in terms of economic development, urban construction, population structure, educational resources, and technological innovation. Chambers and Partners is a globally recognized legal service evaluation agency. Its Chambers China list covers the most powerful and internationally renowned law firms and individual lawyers in China, ranked by practice area, client feedback, and international influence. The National Thousand Foreign-Related Lawyers Talent Pool is an initiative led by China's Ministry of Justice. It compiles comprehensive profiles of lawyers with strong foreign-related expertise, including their language skills, international education/work experience, foreign-related case experience, and specialized practice areas. China Legal Service Network is a national legal service information platform sponsored by the Ministry of Justice; it centrally displays data such as the distribution of national legal service resources, basic information of law firms, service scope, and practice qualifications.

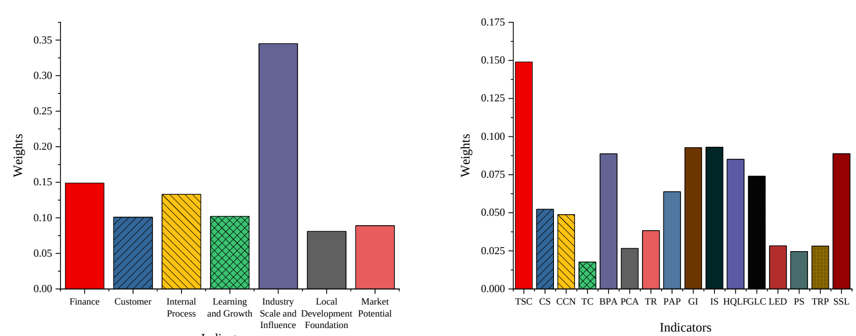
Experimental environment and parameter settings

This study builds an experimental platform under the Windows 10 operating system. It mainly uses Python 3.12 as the development tool and the TensorFlow 2.17 framework for the construction and training of neural network models.

The TS-BP model designed in this study adopts a traditional three-layer feedforward BPNN structure, encompassing 3 input layer nodes, 7 hidden layer nodes, and 1 output layer node. The number of hidden layer nodes is initially set between 3 and 14, and the optimal structure is determined to be 7 nodes through cross-validation to balance model complexity and generalization ability. The activation function between each layer is the Sigmoid function to enhance the model's nonlinear fitting ability. The model's learning rate is set to 0.01, the maximum number of iterations is 1000, the optimizer uses the classic gradient descent algorithm, and the loss function is the MSE. During training, if the decrease in loss is less than the set threshold for several consecutive iterations, an early stopping mechanism is adopted to avoid over fitting. All input features are normalized to eliminate the interference of dimension differences on model training.

Performance evaluation

The results of the balanced scorecard-based performance evaluation indicator weights are revealed in Figure 3



(a) Primary Indicators

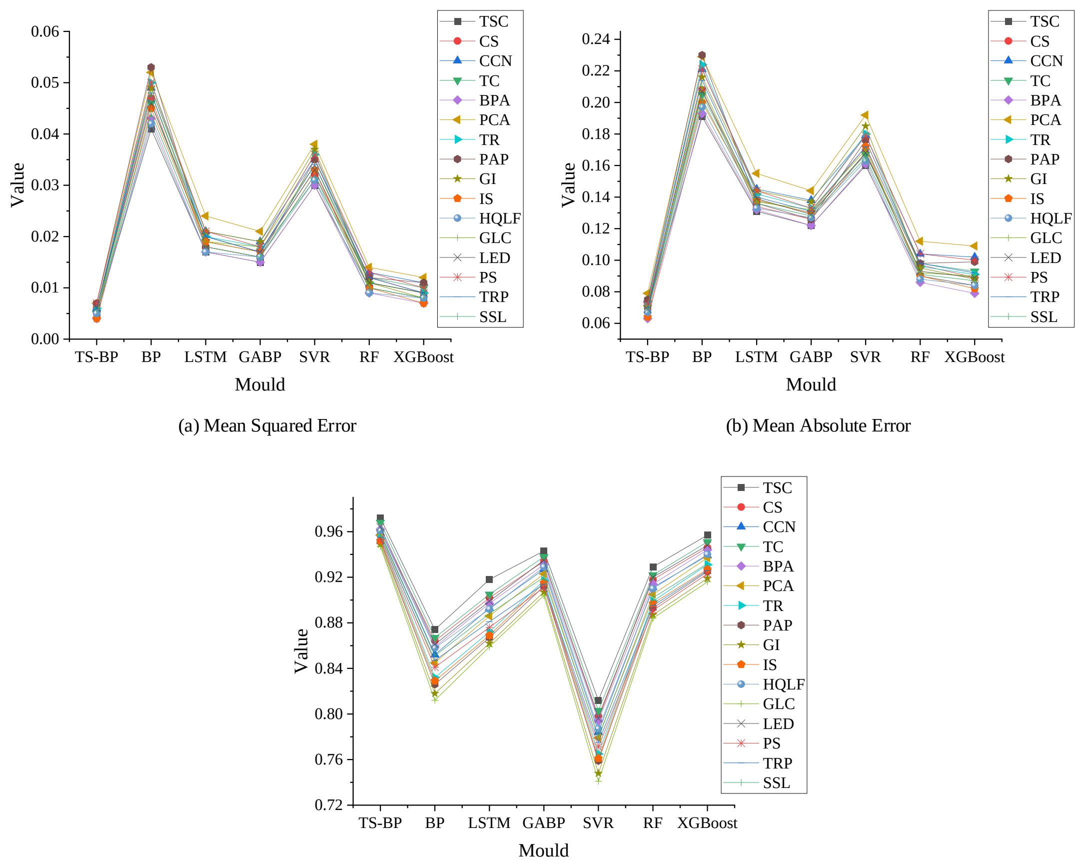
(b) Secondary Indicators

Figure 3: Results of the performance evaluation indicator weights based on the balanced scorecard

An analysis of Figure 3 shows that among the indicators for evaluating the global expansion capability of law firms, the weight of industry scale and influence is the highest (0.345); this indicates that it is the most critical primary indicator, far higher than other indicators such as finance (0.149) and internal processes (0.133). Among the secondary indicators, the top three in terms of weight are TSC (0.149), IS (0.0931), and GI (0.0928); this illustrates that the business source capability, organizational size, and international talent reserve of law firms are the core factors determining their global expansion potential; while the team collaboration capability is only 0.0177, showing its relatively small impact. This result reflects the decisive role of external influence and talent structure in the global layout of law firms.

This study uses 6 mainstream prediction models to model and compare the key indicators in the global expansion capability of law firms. These comparison models include standard BP, Long Short-Term Memory (LSTM), Genetic Algorithm optimized BP (GABP), SVR, RF, and Extreme Gradient Boosting (XGBoost). To comprehensively evaluate the advantages and disadvantages of each model in prediction performance, three commonly used regression evaluation indicators are selected for comparative analysis, encompassing MSE, Mean Absolute Error (MAE), and R-squared (R^2). These indicators can reflect the prediction accuracy and stability of the model for the key indicators of law firms' expansion capability. They assess error size, error fluctuation degree, and goodness of fit, providing a quantitative basis for selecting the optimal prediction model. The comparison results of different models' evaluation and prediction effects on various secondary performance indicators are suggested in Figure 4.

Figure 4: Comparison results of evaluation and prediction effects of secondary performance indicators



(a) Mean Squared Error

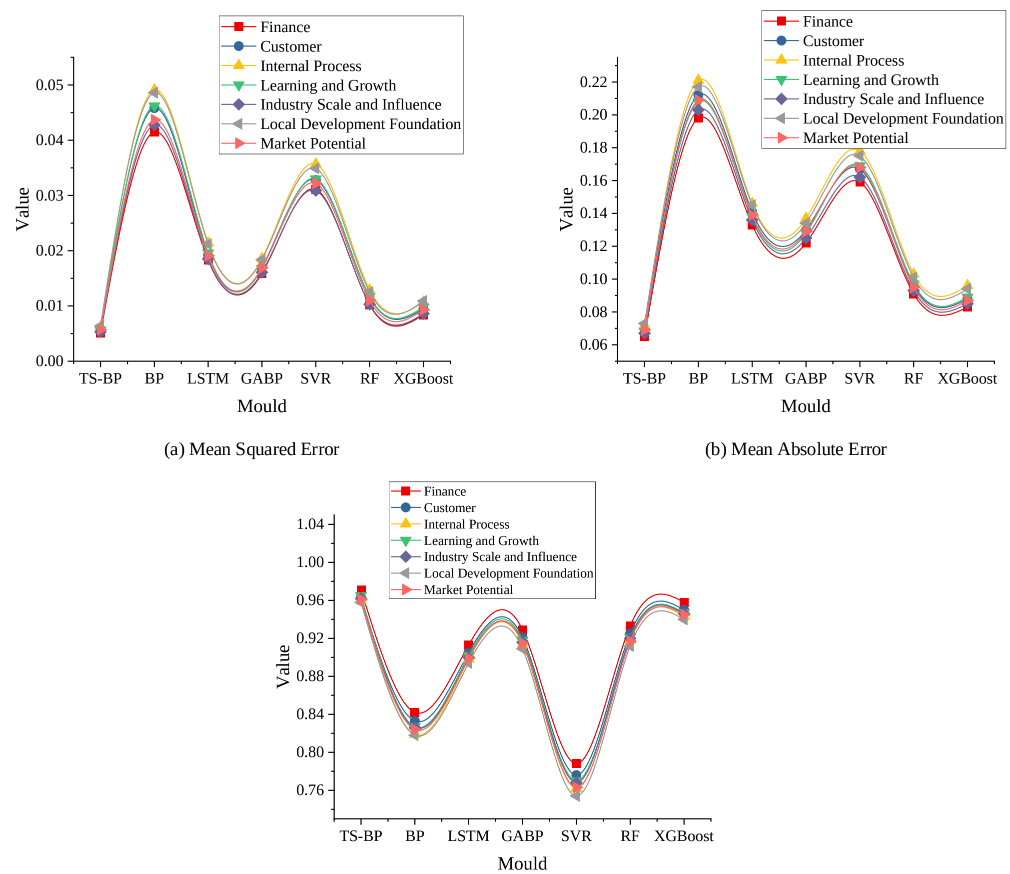
(b) Mean Absolute Error

(c) R-squared

The data in Figure 4 indicates that the proposed TS-BP model's value is significantly lower than that of other models. The proposed model achieves the highest accuracy, especially in indicators of industry scale/influence (with a GLC of 0.006, a GI of 0.005, and an IS of 0.004) and internal process indicators (BPA = 0.004); It shows remarkably reduced errors compared to the traditional BP model. The predictive ability of RF and XGBoost for non-economic indicators is markedly weaker than that of TS-BP. The TS-BP model exhibits the lowest MAE in all secondary indicators, demonstrating its superior prediction accuracy and stability. As integrated learning models, XGBoost and RF perform second best, with good generalization ability and robustness. However, the traditional BP and SVR models have larger errors and insufficient prediction stability and accuracy, especially performing poorly in indicators (CCN and PCA), making them unsuitable for the accurate prediction of complex indicators. The TS-BP model has the highest R^2 value in all secondary indicators, indicating that it has the strongest fitting ability and the most accurate and stable prediction results. The fitting degree of XGBoost in most indicators is close to that of TS-BP, making it suitable as a high-performance alternative. The BP and SVR models have weak fitting ability, which struggles to meet the needs of accurate prediction of multi-dimensional performance indicators in complex legal affairs.

The comparison results of each model's evaluation and prediction effects on diverse primary performance indicators are illustrated in Figure 5.

Figure 5: Comparison results of evaluation and prediction effects of primary performance indicators



(a) Mean Squared Error

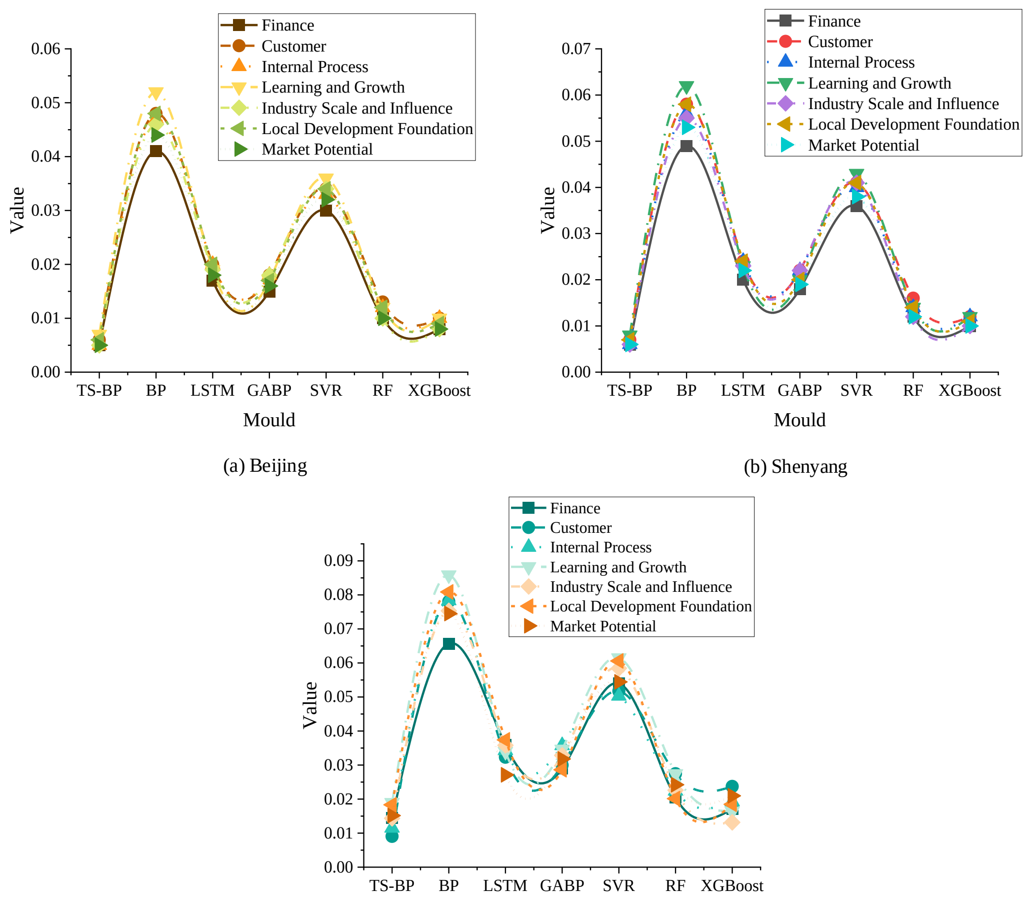
(b) Mean Absolute Error

(c) R-squared

In Figure 5, the TS-BP model has the lowest MSE (0.0051-0.0064) among all primary indicators, illustrating that it performs best in precision control. Followed by XGBoost and RF, these two integrated learning models perform stably, outperforming traditional machine learning models such as SVR and BPNN. In contrast, the BP model has the largest error, indicating its poor generalization ability and unstable prediction, especially showing the weakest prediction effect in aspects such as internal processes and local development foundation. At the MAE level, compared with other models, the TS-BP model proposed in this study performs optimally, further demonstrating the model's stability and accuracy in controlling prediction deviations. BPNN has the largest MAE, consistent with its performance in MSE, displaying that it has large errors and high deviations, and is no longer suitable for tasks with high precision requirements. LSTM and GABP perform moderately, better than BP and SVR, but inferior to TS-BP and integrated models. The TS-BP model has the highest R^2 (0.958-0.971), meaning that it can explain more than 95% of sample fluctuations and has the best fitting effect. GABP and LSTM also perform well (about 0.9) and have certain generalization ability. In contrast, BP and SVR have weaker fitting ability and are difficult to handle the accurate prediction tasks of complex indicators.

Various models' evaluation and prediction results on law firms' global expansion strategic performance in different regions are depicted in Figure 6.

Figure 6: Evaluation and prediction results of global expansion strategic performance of law firms in diverse regions



(a) Beijing

(b) Shenyang

(c) Baoding

Figure 6 reveals that the TS-BP and XGBoost models exhibit optimal performance in all regions. In Beijing, a first-tier city, the average MSE of TS-BP and XGBoost is controlled below 0.01. Compared with the BP model (around 0.05), the prediction error is reduced by more than 75%, indicating that in regions with high data quality, these models have higher fitting accuracy for performance evaluation. In second-tier cities such as Shenyang, the average MSE of TS-BP remains in the range of 0.006–0.008, while the BP model's error increases to 0.049–0.062, with a still obvious gap. This shows that excellent models can maintain good stability even in regions with medium data quality. In third-tier cities such as

Baoding, the average MSE of the BP model is the highest at 0.086. In contrast, the TS-BP and XGBoost models are still controlled in the range of 0.012–0.023, with an error reduction of more than 70%. In addition, traditional machine learning models such as SVR and GABP show error fluctuations in middle and low-tier cities, indicating sensitivity to data noise. From a numerical perspective, the TS-BP model has the lowest average error and the smallest fluctuation in first-tier, second-tier, and third-tier cities. This reveals that the TS-BP model is the most suitable prediction method for evaluating the global expansion performance of law firms. This also suggests that law firms can select more robust models according to regional data quality to optimize the formulation of global expansion strategies.

Discussion

This study presents remarkable advantages in performance evaluation and prediction methods compared with previous studies. Existing studies mostly use the combination of the entropy weight method, DEA, and BPNN to construct performance evaluation models. However, there are certain limitations in multi-dimensional, soft indicator identification and prediction accuracy. In contrast, this study introduces TS in the input structure to optimize the BPNN model, which improves prediction accuracy while significantly enhancing the model's generalization ability and stability. Compared with traditional methods, the TS-BP model performs better in MSE, MAE, and goodness of fit under various indicators; especially when facing non-economic indicators with strategic complexity in the legal service field, the prediction results are more stable. This study expands the multi-dimensional indicator system of performance evaluation. In particular, it integrates the strategic management perspective into the legal service industry, enriching the evaluation content and the methodological foundation. Meanwhile, it improves the accuracy and application scope of the prediction model through technological innovation. It provides a more reliable and detailed tool for the scientific evaluation and decision support of law firms' global expansion performance. At the same time, it promotes the in-depth integration of performance management theory and intelligent technology, offering important theoretical value and practical significance.

Conclusion

Research contribution

This study focuses on the evaluation of the global expansion strategic performance of law firms. It constructs a multi-dimensional indicator system based on the balanced scorecard and introduces six mainstream prediction models, including TS-BP, XGBoost, and RF for comparative analysis. The research results show that industry scale and influence are the most important primary indicators (with a weight of 0.345). Among the secondary indicators, TSC, IS, and GI rank the top three with weights of 0.149, 0.0931, and 0.0928, respectively; this reflects the core role of law firms' business volume and internationalization capabilities in the global expansion strategy. In terms of model performance, the TS-BP model demonstrates low error and strong stability in all primary and secondary indicators. For example, the MSE of industry scale and influence reaches 0.0053, and the R^2 can reach 0.962, substantially outperforming traditional BP and machine learning models (SVR, GABP, etc.). Especially in the empirical prediction of cities at different levels, the MSE of TS-BP in first-tier cities is lower than 0.01; it is also stably controlled within 0.02 in third-tier cities, showing good generalization ability and regional adaptability. The notable advantages of the proposed TS-BP model in multi-dimensional performance prediction can provide more scientific and accurate decision support for law firms' global strategies.

Future works and research limitations

The deficiency of this study lies in that it only adopts the data from Chinese law firms and does not cover international law firms, which limits the model's global applicability and generalization ability. Future research can be extended to law firms' data from multiple countries and regions, combined with cross-cultural differences, to enhance the universality and accuracy of the model.

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