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The Role of an Intelligent Algorithm-Based Corporate Competitive Strategy Analysis Framework in Driving Economic Growth Models

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SUMMARY: *The identification of enterprise competitive strategy and its mapping to economic growth mode provide support for intelligent decision-making and business analysis. This paper proposes a strategic analysis framework combining gated recurrent unit, graph interactive aggregation and multi-head attention to process heterogeneous enterprise data including financial indicators, competitive signals, text feedback and regional economic variables. A sliding window scheme is used to construct 13260 sets of time samples from 246 enterprises, and the time covers the first quarter of 2016 to the fourth quarter of 2024. The framework uses a dual-output structure to complete the strategic state identification and growth-driven prediction respectively, and divides the strategic state into expansion, coordination and contraction. The cross-feature attention aggregation and dynamic deduction mechanism are introduced to enhance the ability of nonlinear pattern capture and phase response. Experimental results show that the R2 of growth prediction is 0.874, the accuracy is 89.1%, and the Macro-F1 value is 0.852. Compared with RF, XGBoost and MLP baselines, the proposed framework has strong fitting stability, migration consistency and adaptation ability in enterprise scenarios.*

KEYWORDS: *Intelligent algorithm; Strategic analysis; Growth modeling; Multi-source fusion*

1 Introduction

With the expansion of the digital economy, the deepening of industrial coordination and the accelerated pace of competition, enterprise competitive strategies have shifted from empirical judgment to data-driven calculation and analysis. There are linkages between business activities, capital structure, technology input, supply chain feedback, market demand fluctuation and regional economic indicators, and a single financial indicator is difficult to support the stable identification of strategic status. The intelligent algorithm is embedded in the framework of enterprise competition strategy analysis, which can complete pattern extraction, state discrimination and trend mapping in multi-source data environment, and connect enterprise competition behavior to the description of economic growth pattern.

The formation of enterprise competitive strategy is not an isolated event, but the result of the joint action of internal resource allocation and external economic conditions. There are differences in the granularity, statistical frequency and semantic structure of data under different periods, which contain not only structured information such as financial statements and industry indicators, but also semi-structured information such as public opinion text,

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customer feedback and competition signals. In the face of high-dimensional, asynchronous and noisy data environment, the traditional linear analysis method is difficult to fully describe the continuity, mutation and conductivity of strategic adjustment. The computational model needs to deal with time series dependence, feature coupling and cross-level correlation at the same time, so as to provide support for the identification of enterprise competitive strategy and the analysis of growth effects.

Enholm et al. [1] studied the relationship between artificial intelligence and business value, and pointed out that the coupling of data, algorithms and organizational mechanisms can form a computable value generation path. Zhang et al. [2] proposed a risk-aware artificial intelligence and machine learning system framework, which provides a method reference for model stability control in complex decision-making scenarios. Cheng et al. [3] studied the application of multi-modal graph neural network in financial time series forecasting and proved that linkage modeling of heterogeneous variables was helpful to improve the trend fitting ability. Haleem et al. [4] sorted out the application path of artificial intelligence in marketing analysis, indicating that the computational integration of multi-source market information has a realistic basis.

Mukherjee et al. [5] proposed a deep learning algorithm system for stock market prediction, demonstrating the adaptability of nonlinear sequence modeling for complex economic behavior recognition. Tripathi et al. [6] studied the role of machine learning models in the evaluation of business intelligence systems, emphasizing the supporting significance of data-driven analysis for management decisions. Park et al. [7] proposed a customer satisfaction measurement method combining text mining and DEA, which expanded the quantitative utilization method of unstructured business information. Storey et al. [8] summarized the design of human-machine collaborative decision-making system, providing systematic ideas for the combination of intelligent analysis framework and actual management scenarios.

Based on the above research, this paper regards the competitive strategy of enterprises as a computable, identifiable and mappable dynamic object, and constructs an intelligent algorithm framework for the analysis of economic growth patterns. The framework extracts competition intensity, resource allocation efficiency, market response characteristics and economic linkage signals from multi-source enterprise information, and realizes strategic state identification and growth effect characterization through time series representation learning, cross-feature attention aggregation and two-layer output mechanism. The framework provides a unified computing link for enterprise competitive strategy identification, growth effect characterization and scenario verification, and improves the consistency level of cross-scenario output.

2 Related work

The analysis of enterprise competitive strategy changes from empirical judgment to intelligent analysis driven by computational modeling. Faced with the parallel changes of financial indicators, market structure, customer feedback, industry prosperity and regional growth data, strategy identification not only needs to complete feature extraction, but also needs to maintain the consistency between result interpretation and growth mapping. Existing research has accumulated in the aspects of decision support, interpretable artificial intelligence, competitor recognition and text mining, but the unified framework for the linkage analysis of enterprise competitive strategy and economic growth pattern still needs to be integrated.

Sousa et al. [9] studied the expert system supporting strategic decision making, and proposed to co-embed rule base, knowledge representation and decision process into management scenarios. Chaturvedi et al. [10] studied managers' cognition of AI participation in strategic decision-making and pointed out that model credibility affects system adoption. Csaszar et al. [11] conducted research on the decision-making behavior of entrepreneurs and investors, indicating that artificial intelligence can improve the quality of judgment in complex situations. Rathje et al. [12] studied the application of machine learning in organizational and strategic research and proposed a combination path of supervised learning, causal inference, and matching models. Coussement et al. [13] studied the role of explainable AI in enhancing decision making and proposed that the explanation mechanism should be designed synchronously with the model output. Sadeghi et al. [14] studied agile decision making in supply chain networks, and proposed that interpretable artificial intelligence can help improve decision response in dynamic environments. Pahsa[15] studied the decision support system of financial technology and emphasized the importance of heterogeneous business data access. Kostopoulos et al. [16] reviewed the decision support system based on interpretable artificial intelligence, and pointed out that the explanation layer, reasoning layer and application layer should form a stable interface.

Cao et al. [17] studied the application of artificial intelligence in business research and proposed that business analysis models should pay attention to the unification of data structure and decision-making context. Guler et al. [18] reviewed the research on artificial intelligence in the field of business and management and pointed out that machine learning models have moved from single prediction to composite analysis. Wen et al. [19] studied the analysis method of customer sentiment and product competitiveness based on text mining, and proposed that composite review data can enhance the accuracy of competitive situation recognition. Wu et al. [20] studied the SWOT analysis method based on hybrid text mining, and showed that online reviews can be transformed into structured strategic cognition. Werle et al. [21] reviewed the application scenarios, data sources and algorithms of competitor identification, and clarified the evolution path of competitive analysis from rule screening to algorithm identification. Alzate et al. [22] studied the role of online comment mining in the analysis of brand image and brand positioning, and proposed that text semantics can provide fine-grained evidence for strategic differentiation.

In order to more clearly present the differences between the existing representative studies in terms of method types, data objects, evaluation indicators and limitations, Table 1 summarizes and sorts out the relevant studies.

Table 1: Comparison of representative studies

Author	Method	Object	Limitation
[9]	Expert System	Strategic Decision-Making	Insufficient dynamic perception
[13]	Explainable AI	Enhanced decision-making	Weak industry mapping capability
[15]	Decision Support System	Financial business	Limited competitive dimensions
[19]	Text Mining	Customers and products	Insufficient linkage to growth
[21]	Algorithmic Identification	Competitors	Insufficient cross-source fusion
This study	Intelligent algorithm-based framework	Strategy and growth	Strengthened linkage analysis

From the existing results, the related research has completed the extension from rule system to machine learning, from structured indicators to text semantics, from single point recognition to decision support. One kind of research focuses on the generation of decision suggestions, and the description of the dynamic evolution of enterprise competitive strategy is insufficient. Another type of research emphasizes competitive identification or brand positioning, but does not incorporate strategic status and economic growth pattern into the unified modeling link. This paper adopts the combination path of "multi-source enterprise information fusion + intelligent algorithm analysis framework + growth mapping" to enhance strategic identification, growth characterization and scenario adaptation.

3 The design of enterprise competitive strategy analysis framework and economic growth driven modeling based on intelligent algorithm

3.1 Enterprise competitive strategy analysis task definition and frame goal setting

When constructing an intelligent framework for enterprise competitive strategy analysis and economic growth driver modeling, the task definition should not stay at the level of business results aggregation, but the competition identification, state representation and growth mapping should be organized as a unified computing link. Different from conventional analysis that only describes financial fluctuations, the framework goal set in this paper should not only extract competitive signals from enterprise operation, market feedback, industry boom and text public opinion, but also form a strategic state representation that can be entered into the growth model, so as to support the linkage analysis among the enterprise level, industry level and regional level. Enterprise competitive strategy is not a static label, but a dynamic object shaped by resource allocation, market response, technology investment and industrial environment. Only when the unified expression is completed in the computational model, the subsequent state discrimination and growth measurement can have a consistent basis.

As shown in Fig. 1, the overall framework consists of six links: multi-source data input, competition variable extraction and alignment, strategic status coding, competition intensity discrimination, growth role mapping and economic growth pattern output. The multi-source data input end receives financial indicators, market shares, supply chain response, brand evaluation and regional economic variables. The competition variable extraction and alignment module completed time synchronization, scale normalization and semantic matching. The strategic state encoding module compressed the heterogeneous features into a unified vector. The competition intensity discrimination module outputs expansion, coordination and contraction states. The growth role mapping module further estimates the degree of transmission of the strategic state to output, efficiency and synergistic increments, and finally forms the output of the economic growth model. This process puts the strategic analysis results and growth modeling results in the same data link, which helps to weaken the semantic offset between different modules.

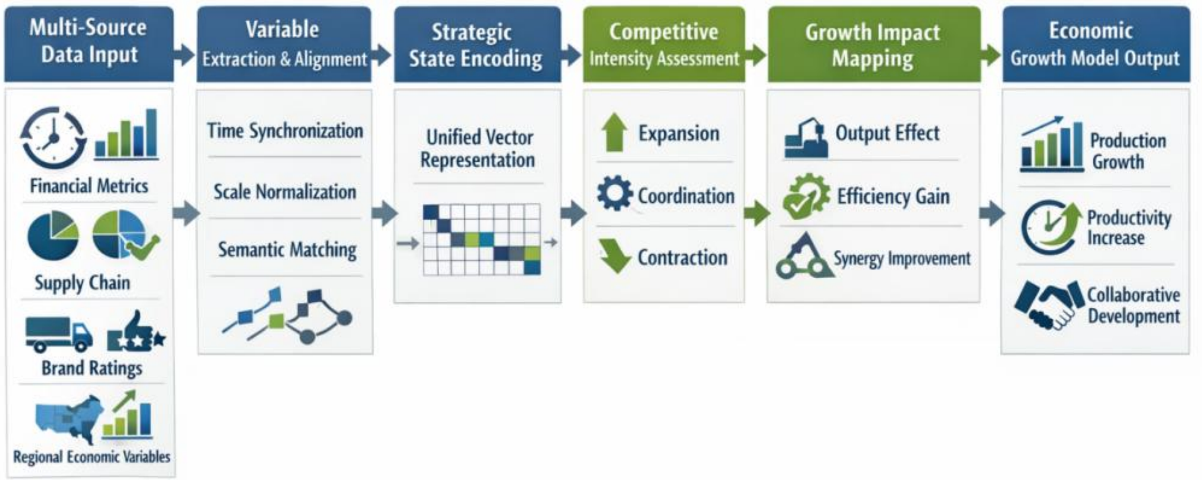

Figure 1: Enterprise competitive strategy analysis task and growth driven modeling process

After competition variable extraction, time alignment and uniform coding, the strategic state representation of firm i at time t can be defined as follows.

$$S_{i,t} = \tanh\left(P_f F_{i,t} + P_m M_{i,t} + P_c C_{i,t} + P_r R_t + b_s\right) \quad (1)$$

where $F_{i,t}$ represents the enterprise finance and operation feature vector, $M_{i,t}$ represents the market competition signal vector, $C_{i,t}$ represents the text semantics and customer feedback vector, R_t represents the regional economic background vector, P_f, P_m, P_c, P_r are the feature mapping matrix, and b_s is the bias term. Equation (1) is used to compress data from different sources and different granularities into a unified strategic state space to ensure that the subsequent discrimination and mapping processes have consistent input.

After obtaining the unified strategic state representation, the driving strength of the strategic state to the next stage economic growth pattern under the joint action of the competitive environment and macro constraints can be further expressed as follows.

$$G_{i,t+1} = \alpha\sigma(U_s S_{i,t}) + \beta\left[\operatorname{softmax}\left(\frac{Q_i K_t^T}{\sqrt{d}}\right) V_t\right] + \gamma Z_t \quad (2)$$

Here, U_s represents the linear transformation matrix from strategic state to growth representation, Q_i, K_t, V_t represent attention query, key and value vectors respectively, d represents the scaling dimension, Z_t represents macroscopic constraint term, and α, β, γ are weight coefficients. Equation (2) is used to describe the driving strength of the strategic state on the growth pattern of the next stage under the joint action of the competitive environment and macro conditions.

Therefore, this paper completes the basic definition of the task of enterprise competitive strategy analysis in this section, and clarifies the goal constraints, input boundaries and output directions that the framework design needs to follow. The following contents will continue to expand on this basis, screen the influential variables of competitive strategy, divide the analysis dimensions, and gradually complete the feature organization and framework implementation of economic growth driven modeling.

3.2 Selection of influencing variables of enterprise competitive strategy and dimension division of analysis

The screening and analysis dimension division of the influence variables of enterprise competitive strategy determine whether the follow-up framework can form a stable, interpretable input basis with growth mapping ability. Different from the method of enumerating indicators only by experience, this paper establishes the variable organization based on the continuous relationship of "competition behavior response-strategic state expression-growth effect transmission", so that the variable set not only reflects the internal business structure of the enterprise, but also covers the external market environment and regional growth background. The competitive strategy of enterprises is not determined by a single indicator, and there is a cross effect between R&D investment intensity, capital turnover efficiency, product competition pressure, brand emotional feedback, supply chain collaboration level and industry boom signal. Only when the structured merging is completed under a unified screening criterion, the subsequent state recognition results are comparable.

In the variable initial screening stage, this paper first calculates the joint association strength between candidate variables and strategic state labels according to the observation sequence after time synchronization, and its expression can be written as follows.

$$a_j = \omega_1 I(x_j, y) + \omega_2 \left|\rho(x_j, y)\right| \quad (3)$$

Here, x_j denotes the j candidate variable, y denotes the strategic state label, $I(\cdot)$ denotes the mutual information term, $\rho(\cdot)$ denotes the correlation term, and ω_1 and ω_2 are the weight coefficients. Equation (3) is used to identify high contribution variables from two levels of statistical correlation and nonlinear interaction to prevent the loss of effective information caused by a single screening criterion.

After completing the initial screening, this paper further calculates the stable contribution degree of the variables in different enterprise scenarios, and constructs the cross-sample weight matrix accordingly, whose expression is:

$$p_{j,s} = \frac{\exp(\bar{c}_{j,s})}{\sum_{q=1}^{m} \exp(\bar{c}_{q,s})} \quad (4)$$

Here, $\bar{c}_{j,s}$ represents the average contribution of the j variable in the sample of the s category of enterprises, and $p_{j,s}$ represents the normalized dimension weight. Equation (4) is used to constrain the variable screening results to maintain a consistent direction under the conditions of different industries, scales and regions, so as to avoid the strong traction of local samples on the overall analysis dimension.

Based on the screening results, this paper divides the analysis dimensions into business foundation dimension, competitive structure dimension, market perception dimension and growth linkage dimension, and forms a unified dimension representation through gated aggregation:

$$H_t = g(W_b B_t + W_c C_t + W_m M_t + W_g G_t + b_h) \quad (5)$$

where B_t, C_t, M_t and G_t represent four types of dimensional vectors respectively, W_b, W_c, W_m and W_g are mapping matrices, and $g(\cdot)$ represents the gating function. Equation (5) is used to map discrete variables into structured input representations that can be entered into the subsequent framework, ensuring that signals from different sources are aligned in the same semantic space.

In order to enhance the interpretability and sparsity after dimension division, this paper introduces the dimension constraint objective:

$$L_{dim} = \eta_1 L_r + \eta_2 \|H\|_1 + \eta_3 \sum_{u \neq v} \cos(h_u, h_v) \tag{6}$$

Here, L_r represents the reconstruction error term, $\|H\|_1$ represents the sparsity constraint term, $\cos(h_u, h_v)$ represents the inter-dimension similarity penalty term, and η_1, η_2, and η_3 are the regulation coefficients. Equation (6) is used to control the aggregation quality within dimensions and the discrimination between dimensions, so that the input structure not only keeps the information intact, but also avoids the diffusion of invalid redundancy.

After the above screening and partitioning, the scattered raw metrics are integrated into structured inputs with clear boundaries. This processing compreses redundant information, retains the key variables required for competitive strategy identification and growth association modeling, and also provides a unified data basis for subsequent multi-source feature representation and framework construction.

3.3 Multi-source enterprise information fusion and feature representation method for competitive strategy identification

Enterprise competitive strategy identification relies on the collaborative input of business data, market data, text feedback and regional growth data, and there are obvious differences in sampling frequency, statistical aperture and semantic granularity of different source information. If the original variables are concatenated directly, it is easy to introduce timing dislocation, scale imbalance and semantic conflict, and then weaken the stability of strategic state discrimination. In order to ensure that the subsequent framework can form a continuous and computable strategic representation, this paper further constructs a multi-source information fusion and feature representation method for competitive strategy recognition based on variable screening and dimension division. This method does not aim at simple summary, but focuses on three links: time alignment, cross-modal mapping and unified coding to complete the structured organization of enterprise competition signals.

For data from different time frequencies and different sources, this paper first completes the time alignment processing based on the unified observation window, and the alignment expression is as follows:

$$\hat{X}_i(t) = \sum_{\tau=-h}^{h} \pi_i(\tau) X_i(t+\tau) \tag{7}$$

Here, τ denotes the set of time offsets, $\pi_i(\tau)$ denotes the interpolation weights of the i mode under offset τ, and $\hat{X}_i(t)$ denotes the alignment result at time t. Equation (7) is used to compress high-frequency disturbances and retain low-frequency trends, so that different modes are comparable under a unified time coordinate.

After the completion of time alignment, this paper further uses attention aggregation to construct the multi-source competition representation, which is calculated as follows.

$$r_t = \sum_{i=1}^{m} \frac{\exp\left(q_t^{\top} k_i / \sqrt{d}\right)}{\sum_{j=1}^{m} \exp\left(q_t^{\top} k_j / \sqrt{d}\right)} v_i \tag{8}$$

Here, q_t, k_i, v_i denote the query, key, and value vectors, respectively, d denotes the scaled dimension, and r_t denotes the fused representation at time t. Equation (8) selects modal responses with higher correlation with the current strategic state through attention weights, thereby weakening the interference of low-contribution features on the representation results.

Considering that the competitive strategy of enterprises contains not only the competitive signals at the numerical level, but also the semantic information in the text feedback, this paper further constructs the unified feature encoding form as follows:

$$E_t = \phi(W_r r_t + W_t T_t + r_t^{\top} A T_t + b_e) \tag{9}$$

where E_t represents the final strategic feature, T_t represents the text semantic embedding, A is the bilinear interaction matrix, and $\phi(\cdot)$ is the nonlinear activation function. Equation (9) is used to preserve the cross relationship between numerical features and semantic features, so that the competitive strategy representation has both structural and semantic information.

In addition, the fused representation also undergoes layer normalization and residual recalipation before being input to the main model, so that the feature amplitude, modal proportion and scene difference are kept within a controllable range. The representation results thus formed can support not only horizontal comparison between enterprises, but also continuous tracking of cross-cycle strategic changes of the same enterprise. At the same time, the unified representation reduces the repeated transmission between the original indicators and retains a clear interface for subsequent growth driver calculation and result interpretation. The overall link has strong engineering adaptability and stability. After the above processing, the original multi-source information is transformed into a time-consistent, semantically coordinated and dimensionally unified strategic representation, which provides stable input for state recognition, growth mapping and dynamic deduction in the subsequent intelligent algorithm framework.

3.4 Intelligent algorithm driven enterprise competitive strategy analysis framework construction

When constructing an intelligent framework for enterprise competitive strategy identification and economic growth driver analysis, three aspects should be considered in determining the model architecture: heterogeneous coupling relationships between multi-source variables, dynamic dependence structure in cross-cycle sequences, and task characteristics of strategic state identification and growth effects describing parallel outputs. Different from a single forecasting model, the framework adopted in this paper should not only maintain the joint expression ability of business foundation, market competition, text feedback and regional growth signal, but also ensure that the strategic analysis results can be continuously transmitted to the growth pattern mapping link. Therefore, a hierarchical intelligent algorithm architecture composed of coding layer, interaction layer and output layer is adopted.

As shown in Fig. 2, the framework consists of six links: multi-source feature input, strategic representation coding, competitive relationship modeling, strategic state extraction, growth driven mapping, and dual-outcome output. The encoding module completes the unified mapping, the relationship modeling module strengthens the expression of the competition structure, the strategic state extraction module identifies the strategic category and intensity, and the growth-driven mapping module further outputs the effect results on the economic growth mode. This structure organizes competitive strategy analysis with growth driver modeling in the same computational link.

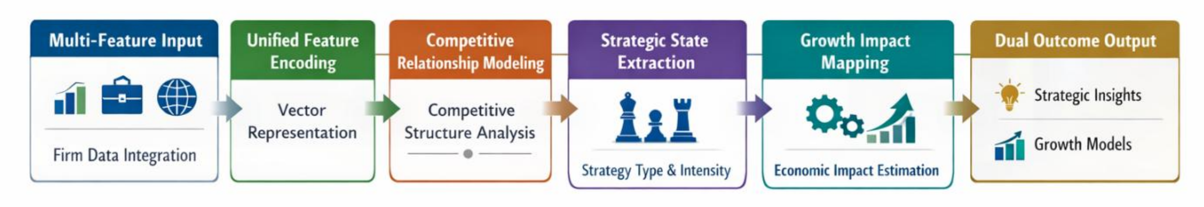

Figure 2: Framework structure of competitive strategy analysis of enterprises driven by intelligent algorithms

After the unified features enter the backbone network, this paper obtains the context representation of the enterprise in the competitive network through graph interactive encoding, which is calculated as follows.

$$H_t = \phi\left(\widetilde{D}^{-\frac{1}{2}}\widetilde{A}\widetilde{D}^{-\frac{1}{2}}X_tW_h + B_h\right) \tag{10}$$

Here, $\widetilde{A}$ represents the competitive incidence matrix after adding the self-connection, $\widetilde{D}$ represents the corresponding degree matrix, X_t represents the input features at time t, W_h represents the trainable mapping parameters, and $\phi(\cdot)$ represents the nonlinear activation function. Equation (10) is used to extract the structural response of the firm in the competitive network, so that the strategic state can absorb the associated information of similar firms and adjacent market units.

After obtaining the structural response, this paper continues to introduce the gated timing aggregation and dual-branch output mechanism, which is expressed as follows.

$$\begin{aligned} U_t &= GRU(H_t, U_{t-1}), \\ \widehat{Y}_t^s &= softmax(W_sU_t + b_s), \\ \widehat{Y}_{t+1}^g &= W_gU_t + b_g \end{aligned} \tag{11}$$

Here, U_t represents the hidden state after the timing update, $\widehat{Y}_t^s$ and $\widehat{Y}_{t+1}^g$ represent the strategic state output and growth driven output, respectively, W_s, W_g, b_s and b_g are the corresponding parameter sets. Equation (11) organizes the competition structure information, time memory information and task branch information into the same framework, so that the model can not only complete the state identification of expansion, coordination and contraction, but also give a continuous driving description of the economic growth pattern.

In the specific implementation, the heterogeneous coding layer is set as a two-layer linear mapping and layer normalization combination, the graph interaction aggregation layer uses a three-head attention structure, the temporal memory layer uses a gated unit with a hidden dimension of 128, and the output layer uses a shared backbone plus dual-branch readout method. The framework controls the parameter scale while maintaining the expressive power, which provides a stable foundation for subsequent strategic role modeling and dynamic deduction.

3.5 Correlation modeling mechanism of corporate competitive strategy on economic growth model

The effect of enterprise competition strategy on economic growth pattern is not directly linear transmission, but gradually through the efficiency of resource allocation, market diffusion speed, industrial synergy intensity and regional response elasticity and other intermediate links. Under different enterprise scenarios, there are obvious coupling among strategic state, competitive pressure and external prosperity. Therefore, the strategic result should not be regarded as a single input item in the growth model, and the correlation modeling mechanism including state representation, transmission weight and growth response should be constructed. Therefore, based on the results of strategy identification, this paper introduces a calculation path combining hierarchical mapping and attention aggregation, so that enterprise competitive strategy can enter the core calculation link of economic growth model.

To ensure that the association modeling has stable input, this paper divides the strategic role path into four sub-channels, which correspond to different role positions in the growth model. The Settings of each channel are shown in Table 2.

Table 2: The associated dimensions of firm competitive strategies and economic growth models

Functional Dimension	Input Content	Growth Implication
Efficiency Transmission	Capital allocation, turnover capability	Affects output efficiency
Diffusion Transmission	Market penetration, brand feedback	Affects demand expansion
Synergy Transmission	Supply chain linkage, industry association	Affects structural connectivity
Constraint Transmission	Policy environment, regional prosperity	Affects growth boundaries

After dimension mapping, the joint representation between strategic state and growth factor can be defined as follows.

$$J_t = \psi\left(W_s S_t + W_e E_t + W_r R_t + W_c (S_t \odot E_t) + b_j\right) \tag{12}$$

Here, S_t represents the competitive strategy state vector, E_t represents the enterprise operation efficiency vector, $\odot$ represents the element-wise interaction term, W_s, W_e, W_r and W_c are mapping matrices, and b_j is the bias term. Equation (12) is used to compress the strategic state and growth environment into a unified association space, so as to ensure that the subsequent growth calculation retains both state information and scenario information.

After obtaining the joint representation, the response value of economic growth in the next stage is further expressed as follows.

$$\hat{g}_{t+1} = \lambda_1 \mathrm{MLP}(J_t) + \lambda_2 \sum_{u=1}^{4} \beta_{u,t} \Delta d_{u,t} + \lambda_3 \xi_t \tag{13}$$

Here, $\hat{g}_{t+1}$ represents the growth response prediction value, $\mathrm{MLP}(J_t)$ represents the nonlinear growth mapping term, $\beta_{u,t}$ represents the action weight of the u dimension at time t, $\Delta d_{u,t}$ represents the incremental signal of the corresponding dimension, ξ_t represents the external disturbance compensation term, and λ_1, λ_2 and λ_3 are the task balance coefficients. Equation (13) is used to describe the transmission strength of the enterprise competitive strategy acting on the growth model through different channels, so that the growth results not only reflect the strategic changes, but also maintain the sensitivity to external constraints and structural linkage.

After the above correlation modeling process, the competitive strategy state of the enterprise is transformed into a structured input that can directly participate in the growth calculation. The growth response no longer only depends on a single economic indicator, but absorbs the information of efficiency transmission, diffusion transmission, coordination transmission and constraint transmission. At the same time, the hierarchical correlation structure can also weaken the interference of single index fluctuation on the overall judgment, so that the output can maintain good stability and explanation clarity under the conditions of industry differences and cycle changes.

3.6 Dynamic deduction and adaptive adjustment mechanism of enterprise competitive strategy analysis results

The results of enterprise competitive strategy analysis have the common characteristics of stage fluctuation, scene migration and response lag in operation. Therefore, the dynamic deduction and adaptive adjustment mechanism need to deal with three types of information at the same time: state continuation, growth feedback and environmental disturbance. Based on the above modeling of the relationship between strategic state identification and growth, this paper introduces a deduction unit for continuous time period updating, so that the system can complete the recursive calculation according to the historical strategic representation, current growth response and external environment migration, and maintain a stable description of the strategic evolution path at the output end.

For the inferred state of the current period, this paper uses gated recursion to organize the historical information and the current input, and its state update form is as follows:

$$P_t = \Lambda_t \odot R_{t-1} + (1 - \Lambda_t) \odot \tanh\left(W_p J_t + U_p E_t + b_p\right) \tag{14}$$

Here, P_t represents the current deduction state, R_{t-1} represents the state in the last time period, J_t represents the joint representation of strategy and growth, E_t represents the environmental disturbance vector, Λ_t represents the adaptive update gate, W_p, U_p and b_p are parameter sets. The function of this equation is to control the fusion ratio of the historical strategic trajectory and the current growth signal, so that the system maintains a balance between state continuation and phase jump.

After obtaining the recursive state, this paper further constructs the trend deduction term, which is used to estimate the cumulative effect of strategic results on the future growth trajectory, and its expression is as follows:

$$D_{t+\Delta} = \sum_{\delta=1}^{\Delta} \omega_\delta \ \phi(V_d R_{t+\delta-1} + B_d C_{t+\delta} + b_d) \tag{15}$$

Here, $D_{t+\Delta}$ represents the deduction result of the future Δ period, ω_δ represents the time interval weight, $C_{t+\delta}$ represents the constraint signal of the future stage, V_d, B_d and $b_d$are the mapping parameters, and $\phi(\cdot)$ represents the nonlinear function. The function of this formula is to extend the single-period strategic state to a multi-period growth response sequence, so as to retain the continuous accumulation characteristics of the role of enterprise competitive strategy.

Considering that the industry environment of the enterprise and the regional economy will continue to change, this paper adds an adaptive adjustment term to the output, and carries out online correction of the original deduction results. The calculation form is as follows:

$$A_t = \mu_t \odot D_t + (1 - \mu_t) \odot \Psi\left(H_t^{ctx}, G_t^{obs}\right) \quad (16)$$

Here, A_t represents the final output after adjustment, D_t represents the original deduction result, H_t^{ctx} represents the scene context representation, G_t^{obs} represents the observed growth feedback, μ_t represents the dynamic weight, and $\Psi(\cdot)$ represents the correction function. The function of this formula is to update the deduction results according to the actual feedback, and reduce the deviation caused by the static parameters under the condition of scene migration.

Through the above dynamic deduction and adaptive adjustment processing, the results of enterprise competitive strategy analysis no longer stay at a single time point identification output, but are extended to a continuous calculation sequence that can be continuously updated with the growth feedback. The mechanism retains historical evolution information while absorbing current scene changes, so as to form a stable connection between strategic state, growth response and environmental disturbance. The obtained results can not only support the subsequent verification of growth effects, but also provide a unified basis for cross-scenario comparison and parameter update, so as to further extend the analysis framework of enterprise competitive strategy to the analysis of economic growth mode.

4 Experimental verification and model performance analysis

4.1 Experimental data source, sample construction and operating environment Settings

In order to verify the effectiveness of the enterprise competitive strategy analysis framework for modeling economic growth patterns, this paper uses multi-source heterogeneous data to carry out experiments. The data sources include financial statements of listed companies, industry competition structure data, online comment texts, regional economic statistics, and policy public data. The time range covers the first quarter of 2016 to the fourth quarter of 2024, and the linkage characteristics of competitive strategy adjustment and growth response in different stages can be observed.

The sample construction follows three criteria: continuous disclosure, completeness, and identifiability. Sample enterprises should continuously disclose core business indicators, and the missing rate of key fields should be controlled within 5%. During the sample period, there are some strategic behaviors such as R&D investment change, market expansion, capital reorganization or channel adjustment. The industry distribution covers four scenarios: manufacturing, information services, medicine and health, and energy. A total of 246 enterprises were selected after processing, forming 13260 sets of time series samples.After sample screening and data sorting, Table 3 further presents the distribution of sample enterprises in various industries and the corresponding statistical results of data scale.

Table 3: Distribution of sample enterprises and size of data

Industry Category	Number of Enterprises	Average Quarterly Feature Count	Number of Strategic Adjustment Events
Manufacturing	92	34	1287
Information Services	61	31	1016
Pharmaceutical and Healthcare	49	33	874
Energy Industry	44	35	963
Total	246	—	4140

The experimental platform is implemented with Python 3.11 and PyTorch 2.2, the processor is Xeon Silver 4314, the memory is 128GB, and the graphics card is RTX A6000. AdamW optimizer is used in the training phase, batch size is set to 32, initial learning rate is set to 0.0005, and cosine annealing scheduling strategy is used. All features are standardized and labeled before input. The data framework maintains continuity in the time dimension and difference in the industry dimension, and supports parallel training in the computing environment, which can provide a stable foundation for subsequent identification evaluation and growth driven simulation, and reduce the interference of sample noise on the model training process.

4.2 Enterprise competitive strategy identification results and growth effect prediction analysis

In order to evaluate the performance of the proposed enterprise competitive strategy analysis framework in strategic state identification and growth effect prediction, this paper uses mean square error, mean absolute error and coefficient of determination to evaluate the growth response prediction effect, and uses accuracy and macro average F1 value to evaluate the strategic state identification effect. The experiment was divided into 70% training set, 15% validation set and 15% test set, and the training and testing were completed on 13260 groups of samples formed by 246 enterprises. All results were averaged over five independent runs to reduce the influence of random initialization and batch perturbation on the results.

Table 4 shows the performance comparison results of different models on the test set. It can be seen that the proposed framework achieves a mean square error of 0.079, a mean absolute error of 0.201, and a coefficient of determination of 0.874 in the growth effect prediction task, which is better than the comparison methods in the five indicators. Compared with RF, XGBoost and MLP, the proposed framework performs more stable in error control and fitting ability, indicating that multi-source feature fusion, competitive relationship modeling and dual-branch output structure can more fully capture the nonlinear correspondence between the change of enterprise competitive strategy and the response of economic growth.

Table 4: Comparison of firm competitive strategy identification and growth effect prediction results of different models

Model	MSE	MAE	R^2	Accuracy	Macro-F1
Proposed Framework	0.079	0.201	0.874	89.1%	0.852
RF	0.121	0.286	0.756	82.6%	0.781
XGBoost	0.108	0.264	0.791	84.3%	0.806
MLP	0.116	0.271	0.768	83.5%	0.794

From the classification results, the proposed framework achieves an accuracy of 89.1% and a Macro-F1 of 0.852 in the strategic state recognition task, indicating that the model has a good ability to distinguish the three types of states of expansion, coordination and contraction. It also shows that the shared backbone and dual-task output mechanism maintain the accuracy of state recognition while not weakening the expression ability of the growth prediction branch. Especially in the sample section with obvious growth fluctuations, the proposed framework can still maintain high fitting consistency, reflecting strong scene adaptability and result stability.

4.3 Simulation verification of the driving effect of the analytical framework on the economic growth model

In order to further test the driving ability of the enterprise competitive strategy analysis framework to describe the economic growth pattern, this paper carries out simulation verification from two levels of vertical time change and horizontal industry difference. The verification content mainly focuses on the fitting accuracy of the growth response trajectory, the identification effect of the key turning point, and the output stability in different industry scenarios, so as to investigate the adaptation ability of the proposed framework in a dynamic environment.

In this paper, a manufacturing enterprise M-92 with more frequent strategic adjustment is selected as a representative sample, and its growth response sequence from the first quarter of 2017 to the fourth quarter of 2024 is fitted and compared with the XGBoost model. The results show that in the third quarter of 2019, the actual growth response value of the sample enterprises is 0.68, the predicted value of the framework is 0.66, and the predicted value of XGBoost is 0.59. In the external shock stage in the first quarter of 2020, the actual value drops to 0.29, the predicted value of the framework is 0.31, and the predicted value of XGBoost is 0.38. In the demand repair stage of the third quarter of 2021, the actual value rebounded to 0.74, the predicted value of the proposed framework was 0.72, and the predicted value of XGBoost was 0.64. In the channel reconstruction stage in the second quarter of 2023, the actual value is 0.57, the predicted value of the proposed framework is 0.55, and the predicted value of XGBoost is 0.49. According to the quarterly series statistics, the MAE and RMSE of the proposed framework on this sample are 0.034 and 0.049, which are significantly better than 0.081 and 0.107 of XGBoost, indicating that the proposed framework maintains a high trajectory fitting ability in the growth decline, repair and rebalance stages. This is shown in Fig. 3.

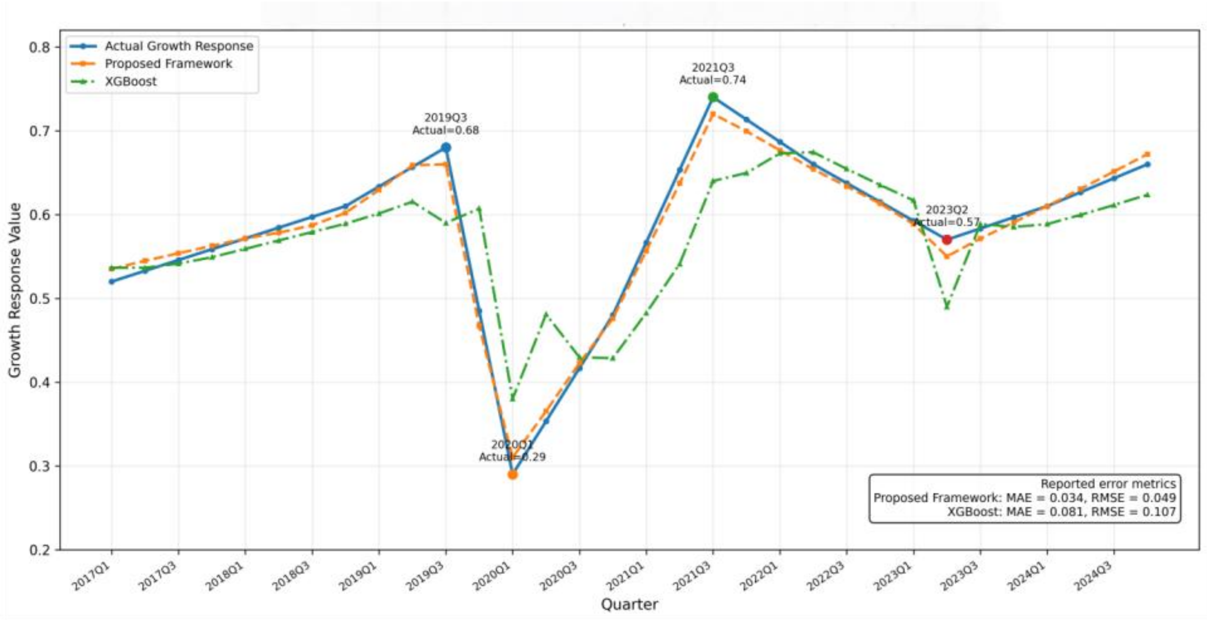

Figure 3: Sample enterprises growth response to actual trend and forecast trend fitting graph

The actual growth curve of the sample enterprises and the forecast curve maintain a good synchronous change relationship. The framework of this paper can accurately track the downward inflection point in the first quarter of 2020 and the rebound inflection point in the third quarter of 2021, the peak deviation is controlled within 0.02, the valley deviation is controlled within 0.03, and the slope change of the curve is basically consistent with the actual trajectory. In contrast, XGBoost has a response lag in the downward phase and a amplitude compression in the repair phase, which is difficult to fully reflect the continuous effect of changes in the competitive strategy of enterprises on the growth path.

In the horizontal simulation part, this paper further selects four types of enterprise samples of information service, manufacturing, medicine and health and energy to compare the influence strength of enterprise competitive strategy changes on the output of growth model under different scenarios. The results show that the actual average growth response value of information service enterprises is 0.71, the average predicted by the framework is 0.69, and the peak response is 0.83. The actual mean value of manufacturing enterprises is 0.58, the predicted mean value is 0.56, and the lowest value is 0.34. The actual peak value of medical and health enterprises in the policy strengthening stage was 0.79, and the predicted peak value was 0.76. The actual mean value of energy enterprises under regional business fluctuations is 0.62, and the predicted mean value is 0.60. According to industry statistics, the average R-squared of the framework on the four types of enterprises is 0.881, 0.867, 0.873 and 0.858, respectively, and the average MAE is 0.029, 0.037, 0.033 and 0.041, respectively, indicating that the model still maintains a relatively stable ability to depict growth drivers in cross-industry scenarios. This is shown in Fig. 4.

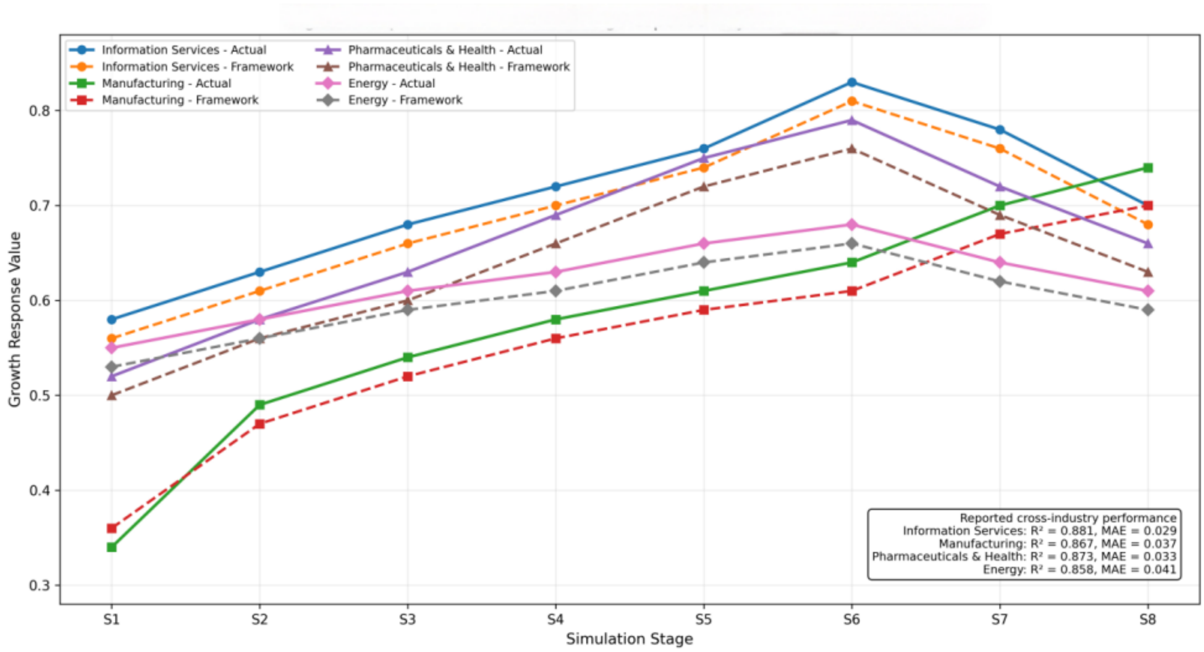

Figure 4: Comparison plots of growth driven response trajectories of firms in different industries

The growth-driven response trajectories of enterprises in different industries show obvious differences. The curve slope of information service enterprises is the largest in the stage of market feedback enhancement, the recovery speed of manufacturing enterprises is relatively slow in the stage of supply chain repair, the pharmaceutical and health enterprises show a higher peak in the policy-driven period, and the energy enterprises show a small fluctuation amplitude. Compared with the traditional method, the average deviation between the output trajectory of the proposed framework and the actual interval is controlled within 0.04, while the average deviation of the comparison model is 0.09. The cross-industry stage boundary identification is clearer, indicating that the proposed framework still has good stability and interpretation consistency under the condition of scene migration.

In general, the framework of this paper not only maintains a better result in the static error index, but also can more accurately depict the stage change, inflection point position and response amplitude in the growth path, indicating that the multi-source feature representation, competitive relationship modeling and dynamic inference mechanism constructed in the previous section can jointly support the stable transmission of enterprise competitive strategy to economic growth mode. It also provides a reliable basis for subsequent analysis of action path and discussion of scene differences.

4.4 Comparative analysis of the proposed framework and traditional analysis methods

In order to systematically evaluate the performance of the proposed enterprise competitive strategy analysis framework in economic growth pattern modeling, this paper conducts analysis from two levels of comparative analysis and internal ablation. The comparative analysis is used to test the advantages of the framework in growth prediction accuracy, strategic state recognition ability and operation stability, and the ablation analysis is used to identify the actual contributions of the three modules of multi-source fusion, competitive relationship modeling and dynamic inference to the results. The evaluation results not only examine the error control level, but also focus on the ability of the model to maintain the inflection point and fluctuation amplitude of growth, so they can better reflect the effectiveness of the framework in continuous computing links.

RF, XGBoost and MLP are selected as the traditional comparison methods, and uniformly trained under the same division of training set, validation set and test set. The results show that the traditional tree model can give more stable fitting results on local samples, but it is insufficient to express the continuous coupling relationship between multi-source features. Although MLP has the ability of nonlinear mapping, it is still insufficient to describe the competition structure and timing dependence. In contrast, the proposed framework organizes competitive strategy identification and growth response prediction in the same backbone network through strategic representation coding, competitive relationship modeling and dual-branch output mechanism, thereby improving the tracking ability of growth path.

As shown in Fig. 5, there are differences in the results of different models on the test set. The R-squared of the proposed framework reaches 0.874, which is higher than 0.756, 0.791 and 0.768 of RF, XGBoost and MLP, respectively. In the strategic state recognition task, the accuracy rate reaches 89.1%, which is higher than 82.6%, 84.3% and 83.5% of the three comparison methods. From the perspective of the error distribution, the proposed framework maintains low bias in the high fluctuation sample interval, indicating that the unified representation formed after multi-source feature fusion can support growth driven modeling. Compared with the traditional method, the proposed framework identifies the stage transition boundary more clearly and responds more smoothly to the growth decline and repair segments.

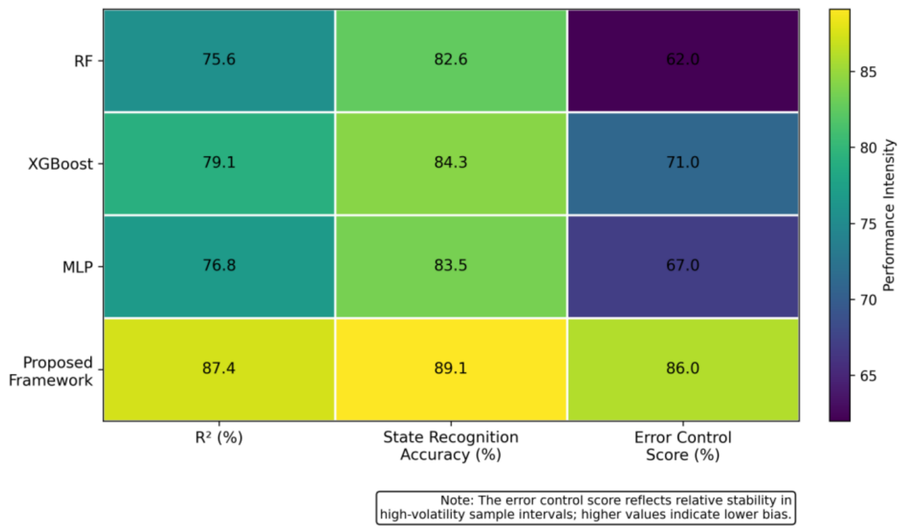

Figure 5: Heat maps of comprehensive performance versus error control for different models

In order to analyze the influence of each module on the overall performance, this paper designs an ablation experiment to remove the multi-source fusion module, competitive relationship modeling module and dynamic deduction module respectively, and compares the model performance changes. As shown in Table 5, the complete framework maintains optimal performance on all five indicators. After removing the multi-source fusion module, the R^2 decreased to 0.831, and the accuracy decreased to 85.0%. After removing the competition relationship modeling module, R^2 and Macro-F1 decreased to 0.842 and 0.821 respectively. After removing the dynamic inference module, MSE and MAE increased to 0.097 and 0.236, respectively. The results show that multi-source fusion, relationship modeling and continuous update mechanism all play a role in growth trajectory fitting and state recognition.

Table 5: Comparison of the results of ablation experiments

Model Configuration	MSE	MAE	R^2	Accuracy	Macro-F1
Full Framework	0.079	0.201	0.874	89.1%	0.852
Without Multi-Source Fusion	0.093	0.229	0.831	85.0%	0.816
Without Relational Modeling	0.089	0.221	0.842	86.1%	0.821
Without Dynamic Inference	0.097	0.236	0.824	85.7%	0.813

From the perspective of computational overhead, the complete framework contains about 1.62 million trainable parameters, and it takes about 38 minutes to complete the training of 13260 sets of samples in the RTX A6000 environment, which increases the training time by about 18% compared with MLP, but significantly improves the accuracy of growth response prediction and the stability of state recognition. In general, the proposed framework is superior to the traditional methods in terms of accuracy, robustness and structural integrity, and provides reliable support for subsequent results discussion and action path analysis.

4.5 Discussion of results

Based on the comprehensive experimental results, it can be seen that the enterprise competitive strategy analysis framework constructed in this paper maintains good output quality in both tasks of growth response prediction and strategic state identification. The index results show that the framework is superior to the comparison methods in the coefficient of determination, error control and classification accuracy, which indicates that the multi-source heterogeneous information is fully utilized in the unified representation space. The simulation results further show that the proposed framework not only has good static fitting ability, but also can accurately track the process of dip, repair and rebalance in the growth path, especially maintain high consistency near the key turning point.

From the perspective of performance sources, the multi-source fusion module improves the scale and semantic differences between heterogeneous variables, the competitive relationship modeling module enhances the structural expression ability between enterprises and industrial environments, and the dynamic inference and adaptive adjustment module improves the continuous tracking ability of the model to stage changes. Ablation results show that after any module is removed, the determination coefficient, accuracy and macro average F1 value will decrease, indicating that the advantages of the framework come from the overall structure collaboration, rather than a single computing unit.

From the perspective of applicability, the framework is suitable for enterprise analysis scenarios that simultaneously carry out strategy identification, growth measurement and trend analysis. In the sample industries such as manufacturing, information services, medicine and health, and energy, the model maintains good cross-scenario stability, indicating that it has a certain compatibility with industry differences and external disturbances.

From the implementation level, although the computational cost of the proposed framework is higher than that of the shallow model, it is still in the acceptable range. More importantly, the output of this framework is a continuous strategy-growth response sequence, which can provide stable support for subsequent analysis of action path and research on scenario differences.

5 Analysis of the driving effect of the framework of enterprise competitive strategy analysis on economic growth mode

5.1 Analysis of the effect path of the analysis framework of enterprise competitive strategy on economic growth mode

The role of the analysis framework of enterprise competitive strategy on economic growth pattern is not a single line transmission, but in the four calculation links of identification, mapping, feedback and diffusion. The strategic state is first transformed into a computable representation through multi-source feature coding, and then enters the growth driven mapping module to form a joint representation together with regional boom, industrial synergy and market feedback. On this basis, the model further sends the information of competition intensity, resource allocation efficiency and external constraints to the growth response unit to generate phased growth output. This process enables strategic changes at the firm level to be stably projected into growth trajectories at the industry and regional levels, thus forming a continuous link from micro behavior to macro outcomes. At the same time, the dynamic inference module continuously receives new business data and environmental signals, and recursively modifies the existing growth path, so that the growth model no longer depends on static parameters, but maintains a synchronous response to realistic changes. From the perspective of action path, the framework of this paper mainly affects the growth results through four directions: efficiency improvement, demand diffusion, structural coordination and boundary constraint. Efficiency improvement plays a role in capital turnover and input-output relationship, demand diffusion plays a role in market penetration and brand feedback, structural synergy plays a role in supply chain linkage and industrial matching, and boundary constraint is responsible for absorbing policy changes and regional economic disturbances. It is the parallel computation of these paths that enables the strategic analysis results to obtain explicit parameter positions and a continuous conduction logic in the growth model. This mechanism makes the action path have a clear parameter drop point, and supports cross-stage comparison, continuous tracking and unified analysis ability improvement under scene migration.

5.2 Differential analysis of economic growth promotion effects under different enterprise scenarios

Influenced by the change of business structure, competition rhythm, resource allocation mode and external constraints, the driving effect of competitive strategy on economic growth mode shows obvious differences in different enterprise scenarios. Manufacturing enterprises usually have strong capital precipitation and capacity constraints, and the impact of strategic adjustment on growth mode is more spread out through equipment investment, supply chain recovery and cost transmission, so the growth response curve is relatively flat, but it lasts for a long time. The asset structure of information service enterprises is lighter, market feedback and brand recognition changes can enter the model backbone faster, and once the strategic state turns to expansion, the growth output often shows a steeper upward slope. Medical and health enterprises are affected by policy support and research and development cycle, and the growth effect has the characteristics of stage aggregation. In such scenarios, the model relies more on the collaborative input of text semantics and regional constraint signals. Energy enterprises are more vulnerable to the impact of price cycle and regional economic changes. Although the growth response is relatively stable, there will be obvious stage rearrangement under sudden disturbances. Based on the above differences, the framework of this paper does not adopt a unified static processing in scenario adaptation, but adjusts the contribution ratio of different dimensions through dynamic weight allocation and context correction mechanism, so that the same competitive strategy signal can obtain a more reasonable growth explanation in different enterprise environments. The resulting output not only retains the industry differences, but also improves the discriminant consistency when comparing across scenarios, which provides a more reliable calculation basis for subsequent deployment and application.

6 Conclusions

This paper focuses on the role of the enterprise competitive strategy analysis framework in promoting economic growth mode, and constructs an intelligent computing system for multi-source heterogeneous data. The system takes strategic state recognition, growth driving mapping and dynamic reasoning update as the main line, organizes the business characteristics, competitive relationship signals, text feedback information and regional growth constraints into a unified representation space, and completes strategic classification, growth measurement and continuous correction in the same backbone network. The experimental results show that the proposed framework is superior to the comparison methods in terms of coefficient of determination, error control and state recognition accuracy, indicating that the combination design of multi-source fusion, relationship modeling and adaptive adjustment can better support the stable transmission of enterprise competitive strategy to economic growth mode.

The limitations of this paper are mainly reflected in three aspects: the sample is still focused on specific industries and listed enterprises, and the coverage of cross-regional and small and medium-sized enterprise scenarios is insufficient. Although text feedback and policy signals have been included in the input, the semantic granularity is still coarse, and the fine-grained event impact has not been fully described. At present, the framework is mainly based on offline training and phased update, and the ability of real-time incremental learning and online deployment still needs to be strengthened.

The follow-up research will continue in three directions. The sample level will further expand the data coverage of cross-industry, cross-region and enterprises of different sizes, so as to enhance the adaptation ability of the framework in complex business scenarios. At the modeling level, fine-grained event representation, spatio-temporal correlation modeling and incremental update mechanism are introduced to improve the response accuracy of the model to sudden disturbances, stage switching and cross-agent linkage. At the implementation level, lightweight deployment, online reasoning and interpretable interface design will continue to be promoted to reduce the parameter scale, training time and computational overhead caused by scenario migration, making the framework more suitable for embedding into enterprise analysis platforms and intelligent decision systems. In general, the analysis of enterprise competitive strategy needs to shift from static index comparison to the processing mode combining continuous calculation and dynamic feedback, which is also the main direction for further follow-up research.

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