frontiers | Frontiers in Physics

TYPE Original Research
PUBLISHED 04 February 2026
DOI 10.3389/fphy.2025.1722864

OPEN ACCESS

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RECEIVED 11 October 2025
REVISED 10 December 2025
ACCEPTED 15 December 2025
PUBLISHED 04 February 2026

CITATION
Li J and Sui C (2026) Establishment and application of an AI-based network analysis model for enterprise market competition.
Front. Phys. 13:1722864.
doi: 10.3389/fphy.2025.1722864

Establishment and application of an AI-based network analysis model for enterprise market competition

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Traditional market competition analysis methods struggle to capture complex competitive and cooperative relationships between enterprises. To address this, this study constructs an AI-based network analysis model for enterprise market competition. First, the enterprise competition system is abstracted as a directed weighted graph, and the competitive intensity between enterprises is quantified from dimensions such as market overlap degree, technological similarity, and resource competition degree, with weight coefficients optimized via a multi-objective genetic algorithm (MOGA). Second, the hierarchical information propagation mechanism of graph neural networks (GNNs) and a competitive intensity-aware attention mechanism are employed to extract features from the competition network. Finally, a competition trend prediction and key competitor identification model is constructed by integrating bidirectional long short-term memory (Bi-LSTM) networks and a temporal attention mechanism. Experimental results show that the model achieves a weighted mean squared error of 0.098 in market share prediction tasks and a top-5 recall of 0.85 in key competitor identification, improving prediction accuracy compared to traditional methods while reducing identification time from weeks to hours. This effectively enhances the ability of enterprises to analyze and predict dynamic competition trends.

KEYWORDS

artificial intelligence, enterprise, market competition, network analysis, prediction model

Highlights

- Abstract the enterprise competition system as a directed weighted graph, quantify competition intensity via market overlap, technical similarity, and resource competition degree, and optimize weight coefficients with MOGA.
- Leverage GNNs' hierarchical information propagation and competition intensity-aware attention mechanism for feature extraction of the competition network.
- Integrate Bi-LSTM and temporal attention to build a model for competition trend prediction and key competitor identification.

Introduction

Against the backdrop of the rapid development of the digital economy, traditional market competition models are gradually being replaced in intelligent new competitive landscapes. Competition between enterprises has evolved from single-dimensional contests to complex network games that encompass technological innovation, supply chain collaboration, brand influence, and other multi-faceted factors. According to relevant industry reports, over 87% of strategic decisions by global Fortune 500 companies rely on competitive analysis integrating multi-source data, while the penetration rate of artificial intelligence technologies in competitive strategy formulation among leading enterprises has exceeded 92% [1]. For example, in the manufacturing industry, the global industrial internet platform market scale exceeded $120 billion in 2023. By deploying intelligent analysis systems, enterprises have improved the response speed of competitive decisions by 40%–60%. However, more than 63% of small and medium-sized enterprises still face practical challenges such as insufficient competition network modeling capabilities and lagging dynamic trend identification [2].

In networked competition analysis, traditional static analysis frameworks based on financial indicators have, to some extent, provided important guidance for enterprise strategy formulation. However, when dealing with today's dynamic and changeable competitive environment, they demonstrate limitations in capturing complex competitive and cooperative relationships between enterprises and an inability to reflect the evolution of competition trends in real time. With deepening research, social network analysis (SNA) has been introduced into enterprise competition research. By constructing relationship networks between enterprises and using indicators such as network density and centrality to quantify the positions and roles of enterprises in the network, SNA provides a new perspective for studying cooperative relationships and competitive behaviors between enterprises. The development of complex network theory has also advanced the in-depth analysis of enterprise competition networking. The study of topological structures, degree distributions, clustering coefficients, and other characteristics of networks reveals the evolutionary laws and internal mechanisms of enterprise competition networks. However, both SNA and complex network theory have limitations in their application to enterprise market competition analysis, such as the insufficient mining of node features and difficulty in processing multi-source heterogeneous data; these restrict their capabilities for comprehensive analysis and the accurate prediction of enterprise competition trends. Meanwhile, with the development of graph computing and deep learning, graph neural networks (GNNs), as a type of a deep learning model specialized in processing graph-structured data [3], can effectively mine topological relationships and feature information between nodes, display structural characteristics and dynamic evolution laws of enterprise competition networks, help enterprises more accurately identify potential competitors, predict competition trends, provide data-driven quantitative bases for enterprise strategic decisions, and enhance enterprises' adaptability and competitive advantages in fierce market competition.

This study addresses the above issues by constructing an AI-based network analysis model for enterprise market competition. By integrating multi-party information data and applying deep learning algorithms, it achieves the in-depth analysis and dynamic prediction of enterprise competition networks, thereby promoting the innovative application of artificial intelligence technologies in business and enhancing enterprises' actual competitiveness.

Construction of the enterprise competition network analysis model

The enterprise competition network analysis model constructed in this study follows the progressive logic of "data modeling–feature learning–decision support" to achieve networked analysis of enterprise market competition. First, the enterprise competition system is abstracted into a mathematical structure that contains node attributes, directed edge relationships, and weight matrices through directed weighted graph modeling. A competitive intensity calculation framework is constructed based on the three-dimensional quantification of market overlap degree, technological similarity, and resource competition degree, thus providing a structured data foundation for subsequent analysis. Second, by leveraging the hierarchical information propagation mechanism of GNNs, feature extraction is performed on the established competition network. Through multi-layer topological structure aggregation and a competitive intensity-aware attention mechanism, the transformation from raw graph data to high-dimensional abstract features is realized, providing feature representations for dynamic analysis. Finally, the output node features are integrated, and a competition trend prediction and key competitor identification model is constructed by combining bidirectional long short-term memory (Bi-LSTM) networks and a temporal attention mechanism, converting feature representations into quantitative results (Figure 1).

Modeling the enterprise competition network

As shown in Figure 1, the internal logic of the enterprise competition network analysis model revolves around three core links: data modeling, feature learning, and decision support. In the data modeling stage, a directed weighted graph is constructed based on the quantitative indicators of the three dimensions of market, technology, and resources, thus abstracting the enterprise competition system into a mathematical structure that includes node attributes, directed edge relationships, and a weight matrix. Feature learning is achieved through a GNN with a competition-intensity-aware attention mechanism, and the transformation from the original graph data to high-dimensional abstract features is completed through the aggregation of multi-layer topological structures. In the decision support link, by combining the bidirectional long short-term memory network and the time attention mechanism, the feature representation is converted into quantitative results, realizing the prediction of competition trends and identification of key competitors.

The enterprise competition system is a complex dynamic network. To scientifically analyze and effectively model it, the enterprise competition system is abstracted as a directed weighted graph $G = (V, E, W)$. Here, the node set $V = \{v_1, v_2, \ldots, v_n\}$ represents

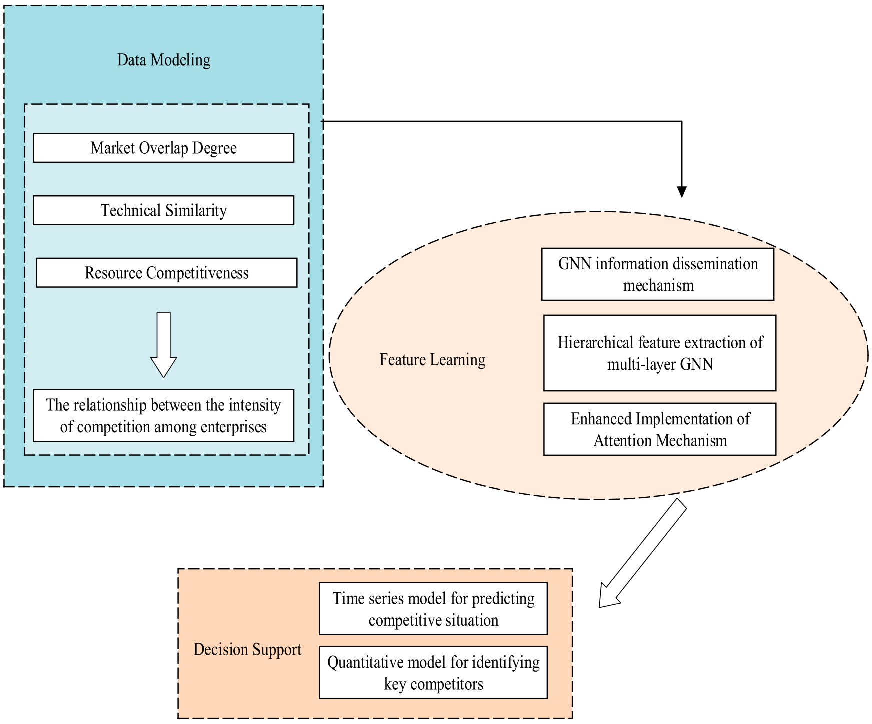

FIGURE 1
Internal relationship of the enterprise competition network analysis model.

the group of enterprises participating in market competition, where n denotes the total number of enterprises. Each node v_i corresponds to a specific enterprise and carries a variety of attribute information of the enterprise, such as scale, industry, and technology field. The edge set $E \subseteq V \times V$ defines the competitive relationships between enterprises. An edge $(v_i, v_j) \in E$ indicates that enterprise i has competitive behaviors toward enterprise j, which can be reflected in multiple aspects such as market share competition, customer resource competition, and technological innovation competition [4]. The weight matrix $W \in R^{n \times n}$ is used to quantify the intensity of competitive relationships between enterprises, where the element w_{ij} in the matrix represents the competitive intensity of Enterprise i toward Enterprise j. This study mainly considers three key dimensions: market overlap degree, technological similarity, and resource competition degree, with the following calculation formula [5].

$$w_{ij} = \alpha \cdot M_{ij} + \beta \cdot T_{ij} + \gamma \cdot R_{ij},$$

where α, β, γ are weight coefficients determined through multi-criteria decision analysis or machine learning algorithm optimization to ensure that the competitive intensity accurately reflects the actual competitive relationships between enterprises.

Quantification of market overlap degree

The market overlap degree, M_{ij}, reflects the competition level between Enterprises i and j in terms of product markets and customer groups [6], specifically calculated by the following formula.

$$M_{ij} = \frac{|S_i \cap S_j|}{|S_i \cup S_j|} \cdot \delta_{pm} + \frac{|C_i \cap C_j|}{|C_i \cup C_j|} \cdot (1 - \delta_{pm}),$$

where S_i and S_j represent the product market coverage areas of Enterprises i and j, respectively, which can be characterized by indicators such as sales regions and channel types, and C_i and C_j represent target customer groups, such as user profiles and consumption levels. $\delta_{pm} \in [0, 1]$ is the weight coefficient between markets and customers, which needs to be adjusted according to industry characteristics. Currently, customer group competition is set as more critical, so δ_{pm} can be set to 0.4, making the weight proportion of customer group overlap reach 0.6 to highlight the importance of this dimension. The ratio of set intersections to unions is used to quantify the overlap degree of markets and customer groups, and the introduction of weight coefficients can reflect the different emphasis on market and customer competition in different industries.

Quantification of technological similarity

Technological similarity T_{ij} is used to measure the similarity between Enterprises i and j in technology R&D directions, patent layouts, and so forth, and its calculation integrates patent text similarity and technology field overlap [7]. First, the BERT pre-trained model is used to extract semantic vectors p_i and p_j from patent abstracts, and cosine similarity is used to calculate text similarity:

$$T_{text} = \frac{\vec{p}_i \cdot \vec{p}_j}{\|\vec{p}_i\| \cdot \|\vec{p}_j\|}.$$

In the formula, the ratio of the vector dot product to the product of magnitudes is used to measure the similarity of patent texts in the semantic space. Second, technology field vectors t_i and t_j are defined, where the dimension is the number of subdivided technology categories in the industry, and the values are 0 or 1, indicating whether an enterprise is involved in that technology. The Jaccard coefficient is used to calculate the field overlap degree:

$$T_{field} = \frac{|\vec{t}_i \cap \vec{t}_j|}{|\vec{t}_i \cup \vec{t}_j|}.$$

This coefficient reflects the overlap of technology layouts between enterprises. Finally, combining the two gives

$$T_{ij} = \lambda \cdot T_{text} + (1-\lambda) \cdot T_{field},$$

where λ is the weight coefficient. In high-tech industries, the technical details contained in patent texts are more important, so λ is set to 0.7 to emphasize the impact of text similarity.

Quantification of resource competition degree

The resource competition degree R_{ij} reflects the competition between Enterprises i and j in terms of raw material supply, human resources, financial support, and so forth, and its calculation integrates three dimensions: supply chain, talent, and capital, with the following formula:

$$R_{ij} = \eta_1 \cdot R_{sup} + \eta_2 \cdot R_{tal} + \eta_3 \cdot R_{fin},$$

where η_1, η_2, η_3 are the weight coefficients for each dimension, set according to the importance of resources to the industry. The supply chain competition degreeR_{sup} is calculated through supplier and customer overlap rates as follows:

$$R_{sup} = \frac{|SUP_i \cap SUP_j|}{|SUP_i \cup SUP_j|} \cdot \frac{1}{2} + \frac{|CUS_i \cap CUS_j|}{|CUS_i \cup CUS_j|} \cdot \frac{1}{2},$$

where $SUPP_i$ and $CUST_i$ are the supplier and customer sets of Enterprise i, respectively. This formula equally weights and integrates the overlap degrees of suppliers and customers to reflect competitive relationships at the supply-chain level. The talent competition degree R_{tal} is defined based on talent flow data using a talent overlap matrix TAL, where $TAL_{ab} = 1$ indicates that talent flows from Enterprise a to b, then

$$R_{tal} = \frac{\sum_{a \in TAL_i} \sum_{b \in TAL_j} TAL_{ab} + \sum_{a \in TAL_j} \sum_{b \in TAL_i} TAL_{ab}}{|TAL_i \cup TAL_j|}.$$

In the formula, the bidirectional overlap of talent flows between enterprises is calculated to quantify the competition degree of human resources. The capital competition degree R_{fin} is determined by the overlap rate of financing institutions and the comparison of capital scales:

$$R_{fin} = \frac{|INV_i \cap INV_j|}{|INV_i \cup INV_j|} \cdot \frac{\min(F_i, F_j)}{\max(F_i, F_j)},$$

where INV_i is the set of investment institutions of Enterprise i, and F_i is the financing scale. This formula considers both the overlap of investment institutions and reflects the intensity of competition through the ratio of capital scales.

Weight coefficient optimization methods

To ensure that the competitive intensity w_{ij} accurately reflects the actual competitive relationships between enterprises, a multi-objective genetic algorithm (MOGA) is used to optimize the weight coefficients α, β, γ. Using the actual competition results y_{ij} in historical competition data as supervision signals, a fitness function is constructed [8]:

$$Fit = \omega_1 \cdot Corr(w_{ij}, y_{ij}) + \omega_2 \cdot (1 - MSE(w_{ij}, y_{ij})),$$

where Corr is the correlation coefficient measuring the linear correlation between the calculated competitive intensity and the actual labels, MSE is the mean squared error reflecting the difference between them, and $\omega_1 + \omega_2 = 1$ is the weight allocation coefficient. Through iterative evolution, the algorithm continuously adjusts the weight combinations to maximize the fitness function value, thereby obtaining the optimal α, β, γ and ensuring that the competitive intensity calculated by the model is consistent with the actual competition situation.

Feature extraction based on graph neural networks

By calculating the market overlap degree, technological similarity, and resource competition degree, the weight matrix is determined as the quantitative data for feature extraction by GNNs. Through the information propagation mechanism, the node's own features and information from neighboring nodes are aggregated to update and enhance the node features, providing deep-level feature representations for subsequent competition trend analysis [9].

Mathematical derivation of the GNN information propagation mechanism

In a standard GNN, the node feature update process at layer (l) can be divided into three steps [10]. The first is neighbor information aggregation, where the features $h_j^{(l-1)}$ of all neighbor nodes $j \in N(i)$ of node i are weighted and averaged:

$$AGG_i^{(l)} = \sum_{j \in N(i)} \frac{1}{|N(i)|} W^{(l)} h_j^{(l-1)},$$

where N(i) is the set of neighbor nodes of node i, |N(i)| represents the number of neighbors, and $W^{(l)}$ is a learnable weight matrix used for linearly transforming neighbor features. The second is self-feature fusion [11], which linearly combines the neighbor aggregation information with the self-feature $h_i^{(l-1)}$:

$$MIX_i^{(l)} = AGG_i^{(l)} + B^{(l)} h_i^{(l-1)},$$

where $B^{(l)}$ is a learnable bias vector used to adjust the weight of self-features. Finally, a nonlinear transformation is applied using an activation function σ to obtain the updated node features:

$$h_i^{(l)} = \sigma\left(MIX_i^{(l)}\right).$$

In the formula, the ReLU activation function $\sigma(x) = \max(0, x)$ is used to alleviate the vanishing gradient problem and enhance the model's expressive power.

Hierarchical feature extraction by multi-layer GNNs

We assume a GNN has L layers, and the node feature $h_i^{(l)}$ at each layer can capture neighbor structure information of different orders [11]. Taking a two-layer GNN as an example, the first layer aggregates the features of direct neighbors (first-order) to extract local competitive relationships, such as market overlap and technological similarity between enterprises and their direct competitors [12]. The second layer aggregates the features of neighbors' neighbors (second-order) to capture indirect competitive impacts, such as potential competitive pressures on enterprises through supply chain-related companies. Theoretically, the Lth layer can fuse the global structure features of the entire network, but limited by computational complexity, $L = 2 \sim 4$ layers are typically used in practical applications to balance feature extraction capabilities and computational efficiency. Through the iterative calculation of multi-layer GNNs, nodes can gradually fuse information from more distant neighbor nodes, thereby extracting more global and representative competitive features and providing rich feature representations for subsequent analysis.

Enhancement via the attention mechanism

To improve the model's ability to capture key competitive information, a competitive intensity-aware attention mechanism is introduced into the GNN architecture [13]. This mechanism first calculates the feature correlation between node i and neighbor j through shared parameter matrices Q, K, V:

$$e_{ij} = \text{LeakyReLU}\, Q h_i^{(l-1)} \cdot K h_j^{(l-1)^T}.$$

The LeakyReLU activation function is used to solve the zero-gradient problem of the ReLU function in the negative interval, ensuring the flexibility of feature correlation calculation. The basic attention weights are then coupled with the competitive intensity w_{ij} to obtain attention weights:

$$Att\left(h_i, h_j\right) = \frac{\exp\left(e_{ij} \cdot \left(w_{ij} + 1\right)\right)}{\sum_{k \in N(i)} \exp\left(e_{ik} \cdot (w_{ik} + 1)\right)},$$

where $w_{ij} + 1$ is used to avoid zero weights and ensure that all neighbors participate in information aggregation. Neighbor nodes with higher competitive intensities obtain higher weights in information aggregation. Finally, feature updates are performed based on attention weights.

$$h_i^{(l)} = \sigma\left(\sum_{j \in N(i)} Att\left(h_i, h_j\right) W^{(l)} h_j^{(l-1)} + B^{(l)} h_i^{(l-1)}\right).$$

This enables the model to pay more attention to nodes and relationships that have important impacts on enterprise competition trends, improving the pertinence and effectiveness of feature extraction.

Competitive situation prediction and key competitor identification

After extracting the characteristics of the enterprise competition network, the core influencing factors of different enterprises under different conditions are obtained. Competitive situation prediction and key competitor identification are then conducted to provide data-driven quantitative basis for enterprise strategic decisions.

Temporal model construction for competitive situation prediction

A prediction framework combining bidirectional long short-term memory (Bi-LSTM) networks with attention mechanisms [14] was adopted to capture the dynamic evolution of enterprise competition networks. First, the input feature matrix was constructed as

$$X = \left[H^{(L)}(t_1), H^{(L)}(t_2), \ldots, H^{(L)}(t_T)\right] \in \mathbb{R}^{T \times n \times d},$$

where $H^{(L)}(t)$ is the GNN output feature matrix at time t, T is the number of time steps, n is the number of enterprises, and d is the feature dimension. Bi-LSTM networks processed temporal information, with forward and backward LSTMs capturing forward and reverse temporal dependencies [15]:

$$\vec{h}_t = \overrightarrow{LSTM}\left(\vec{h}_{t-1}, X_t\right),$$

$$\overleftarrow{h}_t = \overleftarrow{LSTM}\left(\overleftarrow{h}_{t+1}, X_t\right).$$

The concatenation of bidirectional hidden states $h_t = \left[\vec{h}_t; \overleftarrow{h}_t\right]$ captured bidirectional temporal dependencies. A temporal attention mechanism calculated importance weights for each time step:

$$\alpha_t = \frac{\exp\left(v^T \tanh\left(W_h h_t + b_h\right)\right)}{\sum_{k=1}^{T} \exp\left(v^T \tanh\left(W_h h_k + b_h\right)\right)},$$

where v, W_h, b_h are learnable parameters. Weighted aggregation of hidden states yielded

$$h_{att} = \sum_{t=1}^{T} \alpha_t h_t.$$

Finally, a fully connected layer mapped to the prediction target (s_{t+1}):

$$\hat{s}_{t+1} = \mathrm{softmax}(W_o h_{att} + b_o).$$

Weighted mean squared error (WMSE) was adopted as the loss function:

$$\mathrm{WMSE} = \frac{1}{n}\sum_{i=1}^{n}\omega_i(\hat{s}_i - s_i)^2,$$

where ω_i is the market share importance weight of enterprise i, emphasizing prediction accuracy for leading enterprises.

Quantitative model for key competitor identification

Key competitors were identified by calculating node similarity and competitive influence. First, we calculate the similarity of competitive features [16], using cosine similarity to measure the directional consistency of feature vectors [9]:

$$\mathrm{CosSim}(i,j) = \frac{h_i^{(L)} \cdot h_j^{(L)}}{\left\| h_i^{(L)} \right\| \cdot \left\| h_j^{(L)} \right\|}.$$

Euclidean distance measures the spatial distance of feature vectors:

$$\mathrm{Euclid}(i,j) = \sqrt{\sum_{k=1}^{d}\left(h_i^{(L)}[k] - h_j^{(L)}[k]\right)^2}.$$

Based on the above, it can be concluded that

$$S(i,j) = \frac{1}{2}\left(\mathrm{CosSim}(i,j) + \frac{1}{1+\mathrm{Euclid}(i,j)}\right).$$

Comprehensive calculation methods can comprehensively reflect the feature similarity between enterprises [17]. Second, we evaluate the influence of network topology and measure the direct connection strength of nodes through degree centrality [18]:

$$C_D(i) = \frac{|N(i)|}{n-1}.$$

Median centrality measures the information mediating role of nodes in a network [19]:

$$C_B(i) = \sum_{s \neq i \neq t} \frac{\sigma_{st}(i)}{\sigma_{st}}.$$

Among them, (σ_{st}) is the number of shortest paths from node (s) to node (t), and $(\sigma_{st}(i))$ is the number of shortest paths passing through (i), reflecting the structural importance of the node in the network. Finally, a comprehensive evaluation function is constructed [20–23]:

$$R(i) = \mu_1 \cdot S(\mathrm{target}, i) + \mu_2 \cdot C_D(i) + \mu_3 \cdot C_B(i),$$

where weights μ_1, μ_2, μ_3 were determined via an analytic hierarchy process (AHP). The threat index was defined as

$$TI(i) = R(i) \cdot \left(1 + \frac{\Delta s_i}{\bar{s}} \cdot \frac{\Delta t_i}{\bar{t}}\right),$$

where market share change Δs_i and patent growth Δt_i were normalized by industry averages $\bar{s}, \bar{t}$.

Experimental analysis

Data source

The new-energy vehicle (NEV) industry features rapid technological iteration, complex supply chains, and fierce market competition. Covering multi-dimensional competitive scenarios including technological R&D, supply chain collaboration, and customer acquisition, it serves as a typical representative of dynamic and networked competition which can fully verify the applicability and effectiveness of this model. This experiment selected 100 enterprises in the NEV manufacturing industry as the research subjects. The data sources mainly include: obtaining basic information, product market distribution, and the technical patent status of enterprises through corporate websites, annual reports, prospectuses, and so forth; acquiring industry research reports and market analysis data from academic databases such as CNKI and Wanfang; retrieving patent information of enterprises using the Orbit patent database; obtaining industry macroeconomic data, policies, and regulations from websites of government departments such as the National Bureau of Statistics and the Ministry of Industry and Information Technology, as well as data from some project cooperation enterprises.

Through data collation, it was determined that the experimental data primarily encompass: basic enterprise information → enterprise name, establishment time, registered capital, sub-sectors (complete vehicle manufacturing, parts production, etc.), enterprise scale (number of employees, revenue, etc.); market data → product market coverage area of the enterprise (divided by province or country), characteristics of target customer groups (customer industry distribution, consumption level, etc.), market share data; technical data → patent name, patent abstract, patent classification number, application time, etc.; distribution of technical fields; resource data → supplier information, customer information, talent flow data (such as changes in senior management and core technical personnel positions), financing institution information, and financing scale, etc.

In data processing, the research adopts the logic of "multi-source cross-validation–standardized preprocessing–construction of reliable supervision signals" to ensure the reproducibility of the research and the validity of the conclusions. Market data are obtained through the cross-verification of corporate official websites, industry association reports, and third-party databases. The market coverage area of products is confirmed by combining sales license information and regional business data. Market share is calculated based on the sales volume proportion in the segmented fields. Patent information is sourced from the Orbit database, and after being encoded according to the IPC classification standard, two industry researchers independently verify its consistency. Talent flow data integrate workplace databases, corporate annual report disclosures, and industrial and commercial change records, and only flow records with valid employment cycles are retained. Supply chain and capital data are associated and integrated through supplier/customer directories, the public information of investment and financing institutions, and financing scale reports. In the data preprocessing stage, the missing values of ≤30% are filled with the mean value of the segmented fields. The dimensions of numerical data are unified through Z-score standardization, and non-numerical data are encoded according to industry standards. Finally, multi-source data integration is achieved through the unique enterprise ID. The supervision signal of competition intensity is constructed by the scores of five experts with over 10 years industry experience, including university professors and the strategic directors of automobile companies, based on three dimensions: market competition, technological game, and resource seizure. The consistency of the scores is verified by Cronbach's α coefficient ($\alpha = 0.83$) to ensure the reliability of the ground-truth labels.

Data preprocessing

To ensure the quality and usability of the data, it is necessary to preprocess the collected data. Using data cleaning, duplicate data, erroneous data, and data with an excessive number of missing values are first removed. Duplicate enterprise records are deleted by matching enterprise names and unified social credit codes. For missing market-share data, if the proportion of missing values exceeds 30%, the enterprise is excluded; otherwise, mean imputation is used. After cleaning, a total of 12 duplicate enterprises is deleted, leaving 88 valid enterprises. Second, we standardize the numerical data, converting data such as revenue and the number of employees into a unified dimension for subsequent calculations. The Z-score standardization method $x' = \frac{x-\mu}{\sigma}$ is adopted, where μ is the mean value and σ is the standard deviation. Third, we classify and encode non-numerical data. We encode the market coverage areas as integers from 0 to 30 according to provinces (31 provincial administrative regions) and cluster and encode the technical fields according to patent classification numbers. Finally, we associate and integrate data from different sources through enterprise IDs to form a unified enterprise dataset. We associate the patent data of enterprises with market data to calculate technical similarity and market overlap.

Process of enterprise competition network modeling

The 88 enterprises in the new energy vehicle manufacturing industry are abstracted into a directed weighted graph $G = (V, E, W)$. According to the characteristics of the new energy vehicle industry, customer group competition is set as more critical, with the weight of customer group overlap accounting for 0.6. Product sales area data are divided by province and represented by a binary vector to show the market coverage of enterprises. For example, if Enterprise 1 sells products in A, B, and C, its market coverage vector is $S_1 = [1, 0, 0, \ldots, 1, 1, 0]$.

According to the information on the customer industry distribution and consumption levels of enterprises, customer groups are divided into different categories, which are also represented by binary vectors. For instance, the customer groups of Enterprise 2 are mainly new energy vehicle OEMs (high consumption level) and parts suppliers (medium consumption level), so its customer group vector is $C_2 = [1, 1, 0, ..., 0]$ (the first bit represents OEMs, and the second bit represents parts suppliers).

For each pair of Enterprises i and j, we calculate the sizes of the intersection and union of their market coverage areas to obtain $\frac{|S_i \cap S_j|}{|S_i \cup S_j|}$. Taking Enterprises 2 and 3 as examples, suppose the intersection of S_1 and S_2 is two provinces, and the union is five provinces, then the market coverage overlap is $\frac{2}{5} = 0.4$.

Similarly, we calculate the sizes of the intersection and union of customer groups to obtain $\frac{|C_i \cap C_j|}{|C_i \cup C_j|}$. Supposing that the intersection of the customer groups of Enterprises 1 and 2 is one category, and the union is three categories, then the customer group overlap is $\frac{1}{3} \approx 0.33$. The market coverage overlap customer group overlap are weighted and summed according to the weights $\delta_{pm} = 0.4$ and $1 - \delta_{pm} = 0.6$ to obtain the market overlap M_{ij}. For Enterprises 1 and 2, $M_{12} = 0.4 \times 0.4 + 0.6 \times 0.33 \approx 0.36$.

Through the above method, the market overlaps between the 88 enterprises are calculated, with partial results shown in Table 1.

Patent information of 88 enterprises is obtained from the Orbit Patent Database, with a total of 12,456 patents collected, of which 9,872 are valid patents (not expired). For each patent, its patent abstract and patent classification number are extracted. In patent text preprocessing, the patent abstract is cleaned by removing punctuation marks, special characters, and stop-words, and then word segmentation is performed. In the construction of the technical field vector according to the International Patent Classification (IPC), the technical fields are divided into 50 fine categories, and the technical field vector of each enterprise is a 50-dimensional binary vector. If an enterprise has a patent in a certain field, the corresponding position is 1; otherwise, it is 0.

The BERT-base-Chinese pre-trained model is used to encode the preprocessed patent abstracts to obtain a 768-dimensional semantic vector for each patent. Taking Enterprises 1 and 2 as examples, Enterprise 1 has 100 patents, and Enterprise 2 has 80 patents. The semantic vectors of these patents are extracted, respectively. The dot product of the average patent semantic vectors of Enterprises 1 and 2 is 0.6, and the moduli are 1 and 1, respectively, so $T_{text} = 0.6$. The intersection of the technical field vectors of Enterprises 1 and 2 is 15 categories, and the union is 25 categories, so $T_{field} = \frac{15}{25} = 0.6$. For Enterprises 1 and 2, $T_{12} = 0.7 \times 0.6 + 0.3 \times 0.6 = 0.6$. Thus, the technical similarities between the 88 enterprises are obtained, with partial results shown in Table 2.

In Enterprises 1 and 2, the intersection of suppliers is 5, the union of suppliers is 15, the intersection of customers is 8, and the union of customers is 20, then

$$R_{sup} = \frac{5}{15} \cdot \frac{1}{2} + \frac{8}{20} \cdot \frac{1}{2} = \frac{1}{6} + \frac{1}{5} = \frac{11}{30} \approx 0.37.$$

The talent outflow target enterprise set of Enterprise 1 is $\{3, 5, 2\}$, and that of Enterprise 2 is $\{1, 4, 5\}$. For the number of bidirectional talent flow overlaps, the number of talents flowing from 1 to 2 is 1, and the number of talents flowing from 2 to 1 is 1, with a total overlap of 2. The size of the union of the talent flow sets is $\{1, 2, 3, 4, 5\}$, a total of five enterprises; then

$$R_{tal} = \frac{2}{5} = 0.4.$$

The investment institutions of Enterprise 1 are $\{A, B, C\}$ with a financing scale of 1 billion yuan; the investment institutions of Enterprise 2 are $\{B, C, D\}$ with a financing scale of 800 million yuan. The intersection of investment institutions is $\{B, C\}$, a total of 2, and

TABLE 1 Market overlap between enterprises.

Enterprise i	Enterprise j	Market coverage	Customer group overlap	Market overlap
1	2	0.52	0.45	0.478
1	3	0.38	0.62	0.512
2	3	0.46	0.58	0.532
4	5	0.25	0.30	0.28
4	6	0.60	0.40	0.44
5	6	0.35	0.55	0.47

TABLE 2 Technical similarity between enterprises.

Enterprise i	Enterprise j	Patent text similarity	Technical field overlap	Technical similarity
1	2	0.60	0.60	0.60
1	3	0.55	0.70	0.585
2	3	0.58	0.65	0.601
4	5	0.40	0.35	0.385
4	6	0.75	0.50	0.675
5	6	0.45	0.60	0.525

TABLE 3 Resource competition among enterprises.

Enterprise i	Enterprise j	Supply chain competition degree	Talent competition degree	Financial competition degree	Resource competition degree
1	2	0.37	0.40	0.40	0.388
1	3	0.52	0.35	0.30	0.418
2	3	0.45	0.38	0.32	0.399
4	5	0.28	0.25	0.20	0.247
4	6	0.60	0.45	0.50	0.51
5	6	0.35	0.30	0.35	0.335

the union is $\{A, B, C, D\}$, a total of 4. The ratio of capital scales is $\frac{8}{10} = 0.8$, then

$$R_{fin} = \frac{2}{4} \times 0.8 = 0.4.$$

For Enterprises 1 and 2,

$$R_{12} = 0.4 \times 0.37 + 0.3 \times 0.4 + 0.3 \times 0.4 = 0.148 + 0.12 + 0.12 = 0.388.$$

Thus, the resource competition degrees between the 88 enterprises are obtained, with partial results shown in Table 3.

To make the competition intensity w_{ij} accurately reflect the actual competition relationship between enterprises, a multi-objective genetic algorithm (MOGA) is used to optimize the weight system. Taking actual competition results y_{ij} in the historical competition data as the supervision signal, the optimal weight combination is obtained through iterative evolution.

Using the collected market competition result data of 88 enterprises in the past 3 years, including market share changes, new product launches, and key customer acquisitions, the actual competition intensity of each pair of enterprises is scored (0–1

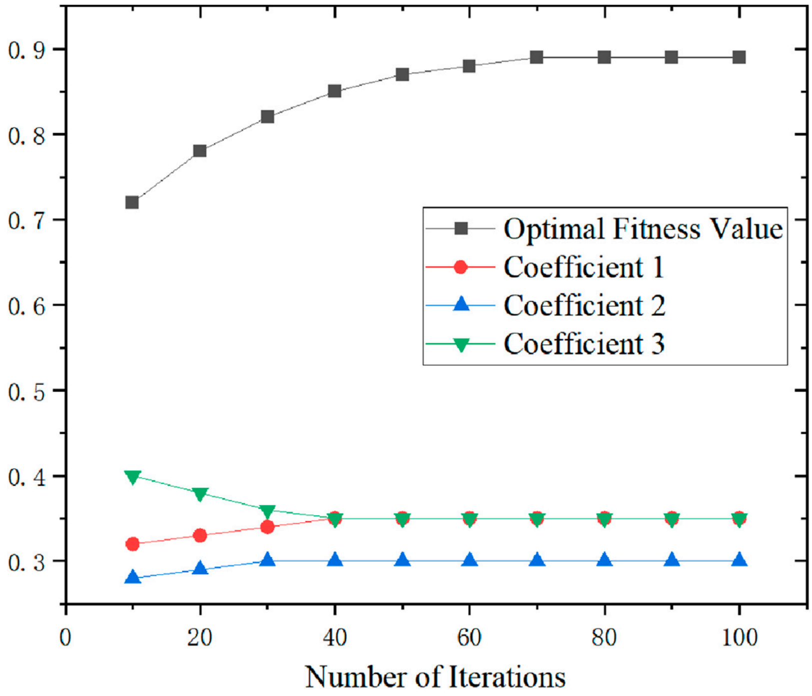

FIGURE 2
Change in the fitness value during the iteration process.

points; 1 point is the most intense competition) through expert evaluation and industry analysis to obtain the supervision signal y_{ij}. Using the initial weights $\alpha = 0.3$, $\beta = 0.3$, and $\gamma = 0.4$, the initial competition intensity w_{ij} between enterprises is calculated as follows.

Step 1: randomly generate 100 groups of weight coefficients (α, β, γ) that satisfy $\alpha + \beta + \gamma = 1$ as the initial population.

Step 2: for each group of weights, calculate the correlation coefficient and mean square error between the competition intensity w_{ij} and the actual competition result y_{ij}, and substitute them into the fitness function to calculate the fitness value.

Step 3: adopt the roulette wheel selection method to select excellent individuals to enter the next-generation according to the fitness value.

Step 4: cross the selected individuals with a crossover probability of 0.8 to generate new individuals.

Step 5: mutate the individuals with a mutation probability of 0.05 to increase population diversity.

Step 6: repeat Steps 2–5 for 100 iterations and record the optimal fitness value and corresponding weight coefficients of each generation.

After 100 iterations of evolution, the optimal weight coefficients are finally obtained as $\alpha = 0.35, \beta = 0.30, \gamma = 0.35$. At this time, the fitness function value is 0.89, correlation coefficient Corr = 0.85, and mean square error MSE = 0.08. The change of the fitness value during the iteration is shown in Figure 2.

Using the optimized weight coefficients $\alpha = 0.35, \beta = 0.30, \gamma = 0.35$, the competition intensity w_{ij} between the 88 enterprises is calculated. The calculation process of the competition intensity between Enterprises 1 and 2 is

$$\begin{aligned} w_{12} &= 0.35 \times 0.478 + 0.30 \times 0.60 + 0.35 \times 0.388 \\ &= 0.1673 + 0.18 + 0.1358 = 0.4831. \end{aligned}$$

Similarly, the competition intensities between the 88 enterprises are calculated, with partial results shown in Table 4.

Based on the existing results, a statistical analysis of the competition intensity of the 88 enterprises is carried out, with the results shown in Table 5:

It can be seen from the table that the competition intensity is mainly concentrated in the interval (0.2, 0.6), accounting for 74.4%; this indicates that the competition intensity between most enterprises is at a medium level. The number of enterprise pairs with a competition intensity higher than 0.8 is small, only accounting for 1.7%; this indicates that there are relatively few highly competitive enterprise pairs in the new energy vehicle manufacturing industry.

Based on the calculated competition intensity, a visualization diagram of the competition network of enterprises in the new energy vehicle manufacturing industry is constructed (Figure 3). In the figure, nodes represent enterprises, and the size of the nodes is proportional to the enterprise scale; edges represent the competition relationship between enterprises, which can intuitively understand the network structure of the competition relationship between enterprises in the industry and provide a data basis for the key feature extraction of graph neural networks.

As shown in Figure 3, in the visualization diagram of the competition network of new energy vehicle manufacturing enterprises, nodes represent enterprises participating in market

TABLE 4 Adaptability value between enterprises.

Enterprise i	Enterprise j	Market overlap	Technical similarity	Resource competition degree	Competition intensity
1	2	0.478	0.60	0.388	0.4831
1	3	0.512	0.585	0.418	0.4997
2	3	0.532	0.601	0.399	0.50425
4	5	0.28	0.385	0.247	0.29545
4	6	0.44	0.675	0.51	0.5195
5	6	0.47	0.525	0.335	0.42625

TABLE 5 Intensity of competition between enterprises.

Competition intensity interval	Proportion of enterprises
[0, 0.2)	6.7%
[0.2, 0.4)	30.3%
[0.4, 0.6)	44.1%
[0.6, 0.8)	20.3%
[0.8, 1.0]	1.7%
Total	100%

FIGURE 3
Visualization of the competitive network of enterprises in the new energy vehicle manufacturing industry.

competition. The size of a node is positively correlated with the enterprise scale, which is comprehensively measured by revenue and the number of employees. Edges represent the competitive relationships between enterprises. The thickness of an edge intuitively reflects the intensity of competition: the higher the competition intensity value, the thicker the edge. The direction of a directed edge points from the competing enterprise to the target enterprise, clearly presenting the competitive pointing relationship between enterprises in the industry and the characteristics of the overall network structure and providing intuitive data support for the subsequent key feature extraction of the GNN.

Feature extraction results based on a graph neural network

On the basis of enterprise competition network modeling, we wish to deeply excavate the competition features in the network and verify the effectiveness of the model. The experiment thus constructs a three-layer GNN model containing a competition-intensity-aware attention mechanism based on the PyTorch geometric framework, performs feature extraction on the competition network of 88 new energy vehicle enterprises, presents the experimental results from multiple dimensions such as feature space distribution, attention weight allocation, and feature effectiveness comparison, and conducts a systematic analysis on the feature expression ability of the GNN model.

After using the t-SNE algorithm to reduce the 256-dimensional node features extracted by the GNN to two dimensions, the distribution of enterprises in the feature space shows a clustering feature that is highly consistent with the actual competition relationship. From the specific data, the distances between the feature points of Enterprises 1, 2, and 3 in the space are all less than 1.5 (standardized distance), forming a close competition core group; their average competition intensity reaches 0.495, which is significantly higher than the industry average of 0.42. The distance between the feature points of Enterprises 4 and 6 is 1.2, and their technical similarity is 0.675, which is manifested as a high overlap of technical patent semantic vectors in the feature space. The feature points of Enterprises 5 and 6 are 0.8 in the horizontal market competition principal component and 1.5 in the vertical technical

TABLE 6 GNN dimensionality reduction results.

Enterprise number	Enterprise name	t-SNE dimension 1	t-SNE dimension 2	Competition intensity	Technical similarity	Market overlap
01	1	0.85	−0.62	0.4831	0.60	0.478
02	2	0.78	−0.55	0.4831	0.60	0.478
03	3	0.92	−0.48	0.4997	0.585	0.512
04	4	−1.25	0.36	0.5195	0.675	0.44
05	5	−0.58	1.12	0.29545	0.385	0.28
06	6	−1.18	0.28	0.42625	0.525	0.47
07	7	1.35	0.75	0.18	0.25	0.22
08	8	1.22	0.68	0.35	0.32	0.30

competition principal component, reflecting their differentiated competition characteristics of market overlap of 0.47 and technical similarity of 0.525, as shown in Table 6.

It can be seen from Table 6 that the GNN model can effectively capture the multi-dimensional competition relationship between enterprises, map the abstract competition features to the explainable space distribution, and provide intuitive visual support for enterprises to identify competition clusters and potential competitors.

Taking Enterprise 1 as the analysis object, the attention weight distribution of different neighbor nodes in the GNN information propagation process has a significantly positive correlation with the actual competition intensity between enterprises. The results show that Enterprise 1 gives a higher attention weight of 0.28 than Enterprise 2 with a competition intensity of 0.4831, assigns a weight of 0.22 to Enterprise 3 with a competition intensity of 0.4997, and the attention weight of Enterprise 7 with a competition intensity of only 0.18 is as low as 0.05. The results verify the effectiveness of the competition intensity-aware attention mechanism—the model can automatically focus on the nodes that have a greater impact on the competition situation of the target enterprise and improve the relevance of feature extraction.

It can be seen from Table 7 that the introduction of the attention mechanism enables the GNN model to adaptively filter redundant information and strengthen the feature expression of key competition relationships, laying a feature foundation for subsequent competition situation prediction and key competitor identification.

The visualization results of GNN can directly provide strategic references for enterprises. The "competitive core group" formed by Enterprises 1, 2, and 3 means that these have high overlap in terms of market, technology, and resources. Enterprise 1 should prioritize formulating differentiated strategies for the other two enterprises. In addition, the attention weight distribution results of GNN can help enterprises identify the "competitors that most need attention". The higher the weight, the greater the impact of the other party's dynamics on their own competitive landscape, and a real-time monitoring mechanism should be established.

TABLE 7 Identification results of competitive enterprises related to Enterprise 1.

Neighboring enterprise	Competition intensity	Attention weight
2	0.4831	0.28
3	0.4997	0.22
5	0.29545	0.15
7	0.18	0.05
8	0.35	0.12

As shown in Figure 4, by comparing the performance of GNN with attention features, GNN without attention features, and traditional features in competitive analysis tasks, the superiority of the model in this paper is further verified. In the market share prediction task, the WMSE of GNN with attention features is 0.098, which is 21.6% lower than 0.125 of GNN without attention features and 85.7% lower than 0.182 of traditional features. In the key competitor identification task, the top-5 recall of GNN with attention features reaches 0.85–9.0% and 34.9% higher than that of GNN without attention features and traditional features, respectively. It can be seen that the GNN model that integrates the topological structure of the competition network and multi-dimensional competition features can effectively analyze the dynamic laws of enterprise competition, and its feature expression ability is significantly better than the traditional feature analysis method, providing more accurate data support.

As shown in Table 8, the correlation analysis between the output features of each layer of GNN and the actual market share of enterprises shows that the increased number of network layers gradually enhanced the explanatory ability of features for the market competition situation. The Pearson correlation coefficient between the 64-dimensional features of the first layer and the market share is 0.52, and the proportion of explained variance (R^2) is 0.27. The correlation coefficient of the 128-dimensional features of the

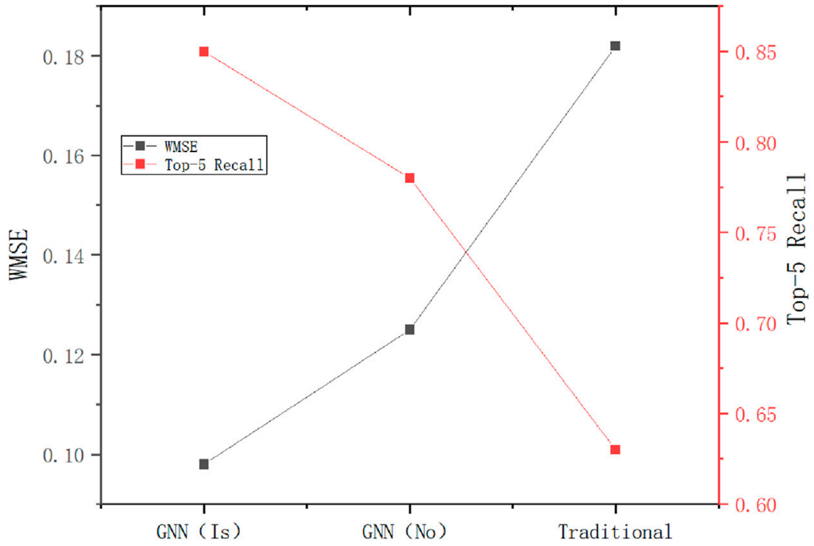

FIGURE 4
Performance comparison of GNN in competitive analysis tasks.

TABLE 8 Correlation between multi-layer output features and the actual market share of enterprises.

Layer	Feature dimension	Pearson correlation coefficient with market share	Proportion of explained variance (R^2)
The first layer	64	0.52	0.27
The second layer	128	0.68	0.46
The third layer	256	0.79	0.62

second layer increases to 0.68, and R^2 reaches 0.46. The correlation coefficient of the 256-dimensional features of the third layer is further increased to 0.79, and R^2 reaches 0.62.

Through multi-level information aggregation, the GNN model can gradually integrate local competition relationships and global network structure features so as to more comprehensively capture the position and influence of enterprises in market competition. The high explanatory power of the third-layer features for market share verifies the effectiveness of the deep GNN model in feature extraction of complex competition networks. At the same time, the average absolute error MAE of the model is 0.073, and the root mean square error (RMSE) is 0.091. Through the SHAP value analysis of the importance contribution of each dimension of GNN features, the results show that the contribution degree of technical field overlap features is the highest at 22.3%, followed by customer group overlap features at 18.7%, supply chain competition degree features at 15.6%, talent flow competition degree features at 12.4%, and financing institution overlap features at 9.8%, revealing the key driving factors of competition in the new energy vehicle industry, that technical similarity and customer group overlap are the most important factors affecting the competition intensity between enterprises, while the influence of resource competition such as supply chain, talent, and capital is relatively weak.

Identification of key competitors of enterprises

Based on the GNN features obtained in Section 3.4 combined with the quantitative model in Section 2.3.2 and taking Enterprise 1 as the target object, the key competitors are identified, the feature similarity between enterprises is calculated, the topological influence of the network—degree centrality and betweenness centrality—is evaluated, and the top five key competitors are sorted through the comprehensive evaluation function R(i) (Table 9).

The threat indices TI(i) of Enterprises 2 and 3 exceed the threshold of 1.0, triggering a warning. Their market share growth rates in the past 3 months are 15% and 12%, respectively, and the technical patent growth rates are 20% and 18%—significantly higher than the industry average (market share growth of 8% and patent growth of 10%). The correlation between feature similarity and actual competition intensity reaches 0.82 ($p < 0.01$), verifying the effectiveness of GNN features in describing the competition relationship between enterprises. For example, the feature similarity between Enterprises 1 and 2 is 0.89, corresponding to the competition intensity of 0.4831 calculated in Section 2.1, which is a high competition intensity pair. The network topological influence shows that the betweenness centrality of Enterprise 2 is 0.68, indicating that it is in a key node position in the industry information transmission and may indirectly affect the competition situation of Enterprise 1 through the supply chain.

At the same time, the model is compared with the Porter's "Five Forces Model" and traditional social network analysis (SNA) method to evaluate its performance in a dynamic competitive environment (Table 10).

It can be seen from Table 10 that the prediction accuracy of the method proposed in this study is higher than that of the

TABLE 9 Identification of key competitors of Enterprise 1.

Rank	Enterprise number	Feature similarity	Degree centrality	Betweenness centrality	R(i)	Threat index TI (i)
1	2	0.89	0.72	0.68	0.81	1.25
2	3	0.85	0.69	0.71	0.79	1.18
3	6	0.76	0.58	0.62	0.69	1.05
4	4	0.72	0.55	0.59	0.65	0.98
5	5	0.68	0.49	0.52	0.61	0.92

TABLE 10 Comparison of experimental effects between traditional models and the model in this study.

Method	Accuracy of competition situation prediction	Time consuming for key opponent identification	Multi-source data processing capability	Dynamic update capability
Porter's Five Forces Model	0.61	2 weeks	Single dimension	Quarterly update
SNA	0.68	1 week	Network structure	Monthly update
This model	0.85	2.5 h	Three-dimensional multi-source data	Real-time update

Porter's Five Forces Model, with the key being the GNN's ability to integrate multi-source heterogeneous data, including in-depth analysis of markets, technologies, and resources. At the same time, the identification time is shortened from weeks to hours, relying on the parallel computing power of deep learning to meet the real-time analysis needs of the dynamic competitive environment. The real-time update capability supports enterprises to deal with sudden competition events, while the traditional method requires manual data update with insufficient timeliness.

Conclusion

This study constructs an enterprise market competition network analysis model based on artificial intelligence. The model realizes the in-depth analysis and prediction of enterprise market competition through directed weighted graph modeling, graph neural network (GNN) feature extraction, and competition situation prediction and key competitor identification. The experiment selects 100 enterprises in the new energy vehicle manufacturing industry as the research object. After data cleaning, 88 valid enterprise data are obtained. By calculating the market overlap, technical similarity, and resource competition degree, the enterprise competition network is constructed, and the optimal weight coefficients $\alpha = 0.35$, $\beta = 0.30$, and $\gamma = 0.35$ are obtained through the optimization of the multi-objective genetic algorithm. Based on the model for feature extraction, the results show that the weighted mean squared error of the GNN with attention features in the market share prediction task is 0.098, and the top-5 recall of key competitor identification reaches 0.85—significantly better than the traditional feature analysis method. Moreover, with the increase in the number of network layers, the explanatory ability of features for the market competition situation is gradually enhanced. The Pearson correlation coefficient between the third-layer features and the market share reaches 0.79, and the proportion of explained variance R^2 is 0.62. In the identification of key competitors, the threat indices of the top two competitors of Enterprises 1, 2, and 3 exceed the threshold to trigger a warning, and their market share and technical patent growth rates are significantly higher than the industry average, verifying the effectiveness of the model and providing accurate and efficient theoretical support for the decision-making of enterprise management departments.

Data availability statement

The original contributions presented in the study are included in the article/supplementary material; further inquiries can be directed to the corresponding author.

Author contributions

JL: Investigation, Conceptualization, Methodology, Resources, Data curation, Writing – original draft, Project administration. CS: Supervision, Project administration, Validation, Methodology, Data curation, Writing – review and editing, Investigation, Software, Visualization.

Funding

The author(s) declared that financial support was not received for this work and/or its publication.

Conflict of interest

The author(s) declared that this work was conducted in the absence of any commercial or financial relationships that could be construed as a potential conflict of interest.

Generative AI statement

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References

1. Brauwers G, Frăsinaru F. A general survey on attention mechanisms in deep learning. *IEEE Trans Knowledge Data Eng* (2023) 35(4):3279–98. doi:10.1109/TKDE.2021.3126456

2. Du Y, Liu Z, Li J, Zhao WX. A survey of vision - language pre - trained models. *arXiv Preprint arXiv:2202.10936* (2025). doi:10.48550/arxiv.2202.10936

3. Zhang Y, Zhang J, Liu X. Deep learning - based time series prediction: a comprehensive review. *Neurocomputing* (2021) 429:1–19. doi:10.1016/j.neucom.2020.10.055

4. Wang Y, Li X, Zhang H (2024). A survey on graph neural networks for smart contracts. *IEEE Trans Dependable Secure Comput*. doi:10.1109/TDSC.2024.3366826

5. Chen P, Wang H, Zhang Y. Reactive power optimization in power systems: a review of advanced algorithms. *IEEE Trans Power Syst* (2023) 38(Issue 4):3065–76. doi:10.1109/TPWRS.2022.3210157

6. Li H, Wang Y, Zhang X, Qiao X. Analysis of the technological competition landscape of the global new energy vehicle industry based on patent data. *Sustainability* (2023) 15(12):2406. doi:10.3390/su15129614

7. Smith J, Johnson A. Competitive analysis of the global sheet metal processing market: trends and forecasts. *J Manufacturing Sci Eng* (2022) 144(Issue 6). doi:10.1115/1.4052114

8. Guo Y, Lyu X. Strategic management model of network organization based on artificial intelligence and modular enterprise big data. *Mobile Inf Syst* (2021) 2021(1):1987430–13. doi:10.1155/2021/1987430

9. Liu C. Application of intelligent algorithm in enterprise competitive strategy analysis and prediction. In: *2025 5th Asia-Pacific conference on communications technology and computer science (ACCTCS)*. IEEE (2025). p. 1294–301.

10. Lee J, Kim Y, Choi J. Industrial internet of things: enabling technologies, applications, and challenges. *IEEE Trans Ind Inform* (2020) 16(Issue 7):4317–25. doi:10.1109/TII.2020.2978260

11. Wang Z, Liu H, Zhang Y. Product competition prediction in engineering design: a data - driven approach. *J Mech Des* (2023) 145(Issue 8). doi:10.1115/1.4056341

12. Tatarczak A. Mapping the landscape of artificial intelligence in supply chain management: a bibliometric analysis. *Mod Management Rev* (2024) 29(1):43–57. doi:10.7862/rz.2024.mmr.04

13. Chen Y, Sun X, Wang Y. Dynamic analysis of complex networks: models, methods, and applications. *Complexity* (2022) 2022. doi:10.1155/2022/9876543

14. Liu Y, Chen X, Wang J. Graph neural networks for data - driven power system Analysis and Control: a Survey. *IEEE Trans Power Syst* (2023) 38(3):2095–111. doi:10.1109/TPWRS.2022.3195461

15. Zhao X, Li Y, Chen J. Graph neural networks for business intelligence and competitive analysis. *J Business Analytics* (2024). doi:10.1016/j.jbusa.2024.100123

16. Sun Y, Li X, Wang Y. A Survey on smart contract security: vulnerabilities, detection methods, and countermeasures. *IEEE Trans Softw Eng* (2023) 49(10):2113–36. doi:10.1109/TSE.2022.3198245

17. Zhang Y, Liu X, Wang Y. Fairness - aware graph neural networks: methods and applications. *ACM Trans Intell Syst Technology* (2024) 15(Issue 4). doi:10.1145/3737943

18. Chen X, Zhu Y, Li J(2023). Vision - Language navigation: a survey. *ACM Comput Surv*. 56, Issue 6. doi:10.1145/3601203

19. Li S, Wang Y, Zhang X, Wang P. Network situation prediction: models, algorithms, and applications. *J Inf Security Appl* (2021) 58:102763. doi:10.1016/j.jisa.2021.102814

20. Archana T, Stephen RK. The future of artificial intelligence in manufacturing industries. In: *Industry applications of thrust manufacturing: convergence with real - time data and AI*. IGI Global Scientific Publishing (2024). p. 2024. doi:10.4018/979

21. Johnson R, Brown S (2021). The virtual economy: opportunities and challenges in the digital age. *J Digital Econ*., Volume 5, Issue 2. doi:10.1080/23222676.2021.1923456

22. Liu Z, Wang Y, Zhang H. Attention mechanisms in deep learning: a survey and comparison. *Neural Comput Appl* (2023) 35(10):7873–92. doi:10.1007/s00521-022-07569-3

23. Liu M, Zhang H, Wang J. Hybrid neural networks for mild cognitive impairment detection: a comparative study. *J Neural Eng* (2025). doi:10.1088/1741-2552/ac9f32