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International Journal of Earthquake Engineering
Anno XLIII - Num. 3 - 2026

Research on Multi-source Data Fusion and Decision Support in Supply Chain Based on Deep Learning

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SUMMARY: *In the context of the accelerated digital transformation of supply chains and the continuous growth of multi-source heterogeneous data, how to break through the information barriers in procurement, production, inventory, logistics, and sales, has become a key issue in intelligent supply chain management. This paper constructs a multi-source data hierarchical modeling framework, adopts single-source feature encoding, cross-source temporal alignment, dynamic weight fusion, and global state representation methods, and further designs shared decision representation, task adaptive gating, multi-task collaborative output, and confidence constraint mechanisms to achieve integrated decision-making for demand identification, inventory judgment, distribution response, and risk warning. Experiments based on 12,000 samples show that the accuracy, precision, recall rate, and F1 value of the proposed method reach 92.8%, 91.9%, 93.4%, and 92.6% respectively, which are 2.5 and 2.9 percentage points higher than the accuracy and F1 value of the Transformer model, and achieve the best comprehensive performance at a threshold of 0.80. This research provides a feasible technical path for the intelligent fusion and decision support of multi-source data in supply chains.*

KEYWORDS: *Deep learning; Supply chain management; Multi-source data fusion; Decision support; Heterogeneous data; Intelligent prediction*

1 Introduction

In the context of the continuous deepening of global supply chain collaboration and the rapid development of the digital economy, the data generated in the supply chain operation process continues to grow, and the data sources have gradually expanded from the traditional procurement, production, inventory, logistics, and sales links to various types of data such as IoT sensing data, platform transaction data, user behavior data, external market data, and policy and environmental information. The extensive aggregation of multi-source data provides a richer information foundation for supply chain state perception, risk identification, and business decision-making, but at the same time, the differences in structural form, time granularity, semantic expression, and quality level among data have become increasingly prominent, leading to data islands, information fragmentation, and decision lag problems that still exist. Based on this, this paper conducts research on the problem of multi-source data fusion and decision support in supply chains, focusing on the collaborative modeling of heterogeneous data, deep feature learning, and decision support mechanism design, aiming to construct a research framework from the data layer, model layer to application layer, to provide method references for improving supply chain operation efficiency, enhancing collaboration capabilities, and supporting management decisions.

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https://doi.org/10.65102/is20261266 Published: 10 June, 2026

1.1 Related Work

In recent years, research on intelligent decision-making and data-driven analysis in supply chains has been continuously deepening. Ma et al. (2025) introduced reinforcement learning methods into the economic decision-making scenarios of supply chains, emphasizing the application value of algorithms in dynamic decision-making and revenue balance, providing new ideas for the research on intelligent decision-making in supply chains [1]. Tabrizi et al. (2025) combined deep learning with the DNDEA model to analyze the prediction efficiency of a two-stage petrochemical sustainable supply chain, demonstrating the strong applicability of deep models in complex supply chain performance prediction [2]. Han and Huang (2025) explored the role of blockchain neural networks in enhancing supply chain trust, pointing out that it has stronger advantages compared to traditional deep learning in terms of trusted collaboration and information security [3]. Wong et al. (2024) from the perspective of risk management, utilized a dual-stage PLS-SEM-ANN analysis framework driven by deep learning to reveal the promoting effect of artificial intelligence technology on the improvement of supply chain agility [4]. Zhou et al. (2025) further applied multi-agent deep reinforcement learning to the collaborative research on demand forecasting and inventory decision-making, reflecting the integrated trend of supply chain collaborative decision-making supported by sensing devices [5]. Bassiouini et al. (2024) focused on the problem of order status identification in complex supply chains, verifying the effectiveness of deep learning in business process identification and status determination [6]. Zhang et al. (2023) conducted research on the interpolation of missing data in supply chain credit risk time series, demonstrating the application potential of deep learning in data repair and risk analysis [7]. Lu (2025) proposed a multimodal deep reinforcement learning method for the global logistics network driven by the Internet of Things, achieving good results in adaptive scheduling and robustness support [8]. Overall, existing research has made progress in economic decision-making, performance prediction, risk identification, inventory collaboration, state discrimination, and logistics scheduling, but most of the results focus on single tasks or local links, and there is still a need for further research on the unified fusion representation of multi-source heterogeneous data and its systematic connection with the decision support mechanism.

1.2 Research Motivation and Contributions

As the operational environment of the supply chain gradually shifts from linear collaboration to networked collaboration, enterprises have accumulated a large amount of business data with diverse sources, different structures, and varying update frequencies in the procurement, production, warehousing, transportation, sales, and after-sales processes. Although existing research has made certain progress in demand forecasting, inventory control, risk identification, and logistics scheduling, there are still common problems in multi-source heterogeneous scenarios, such as scattered data utilization, insufficient integration levels, and insufficient tight connection between model outputs and management decisions. Especially in the real-world environment where procurement, inventory, logistics, and external disturbances interact together, relying solely on a single data source or a single task model often fails to comprehensively reflect the supply chain operation status and is unable to form decision-making basis that is both timely, targeted, and interpretable. Therefore, this paper conducts research from two levels: unified representation of multi-source data and collaborative design of decision support, in order to enhance the intelligent analysis capabilities of the supply chain and the level of business response.

The main contributions of this paper are as follows: First, around the characteristics of multi-source data in supply chains, a unified modeling framework covering business data, status data, and external environment data is constructed, enhancing the collaborative expression ability of heterogeneous information; Second, the deep learning method is introduced to conduct multi-level feature extraction and fusion representation, improving the portrayal effect of complex correlation relationships and dynamic change patterns; Three, based on the integration results, design a decision support method for the supply chain management scenario, forming a complete research chain from data processing, feature learning to decision output; Four, through experiments, verify the effectiveness of the proposed method in supply chain data analysis and decision support, providing references for intelligent research and practical application in related fields.

2 System framework and problem statement

2.1 Supply chain multi-source data system and business scenario modeling

During the operation of the supply chain system, various types of data such as procurement, production, inventory, logistics, sales, and external environment will continuously be generated. These data have significant differences in their structural form, collection frequency, and semantic expression. If analysis is only conducted from a single aspect, it is difficult to fully reflect the overall operation status of the supply chain. Based on this, this paper, from a system perspective, divides supply chain data into data source layer, data processing and alignment layer, scenario modeling and fusion representation layer, and business scenario support layer, and constructs a multi-source data system for decision support. The core idea is to first clean, complete, standardize and time-align data from different sources, then combine node status, business relationships and external disturbance information to form a unified scenario representation. In the business scenario support layer, corresponding sales and order fluctuation information required for demand identification, inventory and replenishment status required for inventory judgment, logistics performance information required for distribution response, and abnormal events and external disturbance information required for risk warning are respectively provided, thereby providing a consistent and targeted data foundation for the four types of tasks.

Under the time window t, the multi-source input of the supply chain can be represented as:

$$\mathrm{X_t} = \{\mathrm{x_t^p}, \mathrm{x_t^m}, \mathrm{x_t^i}, \mathrm{x_t^l}, \mathrm{x_t^s}, \mathrm{x_t^e}\} \tag{1}$$

Among them, $\mathrm{x_t^p}, \mathrm{x_t^m}, \mathrm{x_t^i}, \mathrm{x_t^l}, \mathrm{x_t^s}, \mathrm{x_t^e}$ respectively represent procurement, production, inventory, logistics, sales and external environment data. To enhance the collaborative expression ability of different data sources, this paper further constructs a fusion scene state vector:

$$h_t = \sigma\left(\sum_{k=1}^{K} \alpha_k W_k x_t^{(k)} + b\right), \quad \sum_{k=1}^{K} \alpha_k = 1 \tag{2}$$

Here, W_k is the mapping matrix, α_k is the contribution weight of each data source, and h_t is the supply chain scene fusion representation at time t. Through this modeling method, discrete and heterogeneous raw data can be transformed into learnable and comparable unified state representations, laying the foundation for the subsequent design of deep learning fusion models and decision support methods. The supply chain multi-source data system and business scenario hierarchical framework are shown in Figure 1.

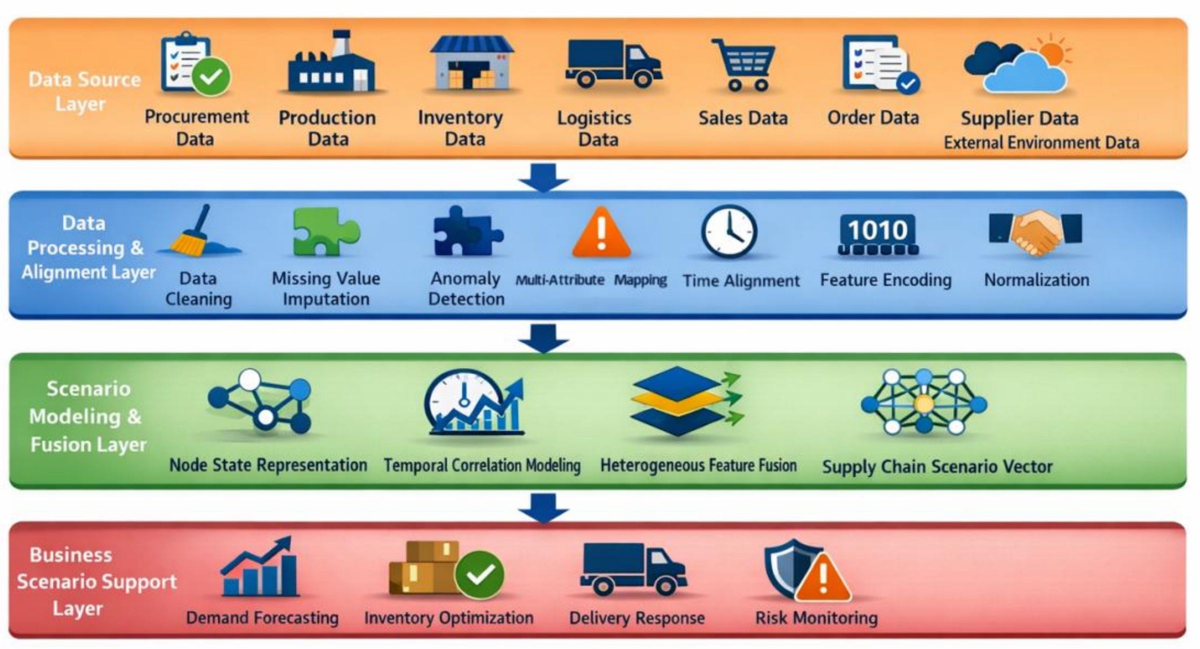

Figure 1: Supply Chain Multi-source Data System and Business Scenario Modeling Hierarchical Framework

2.2 Definition of Decision Support Tasks and Problem Statement

After completing the modeling of the multi-source data system, the core objective of supply chain decision support is to convert the integrated scenario state representation into executable business judgment results. This paper defines the decision support task as: within the given time window t, based on the supply chain scenario vector H_t and its historical state sequence $H_t = \{h_{t-n}, \dots, h_t\}$, output decision results y_t for different business links, including four types of tasks: demand identification, inventory judgment, distribution response, and risk warning. It is uniformly expressed as:

$$y_t = f(H_t, \Theta) \tag{3}$$

where, $f(\cdot)$ represents the decision support model, and Θ represents the set of model parameters. Considering the operational characteristics of the supply chain, this paper divides the decision support task into four categories: demand identification, inventory judgment, distribution response, and risk warning. The overall output is expressed as:

$$y_t = \{y_t^d, y_t^i, y_t^r, y_t^w\} \tag{4}$$

Among them, y_t^d represents the demand identification result, y_t^i represents the inventory judgment result, y_t^r represents the distribution response result, and y_t^w represents the risk warning result. To avoid a single task dominating the overall learning process, this paper introduces the idea of task collaboration and sets weight parameters for different sub-tasks. The comprehensive decision-making objective function is:

$$\mathcal{L} = \sum_{j=1}^{4} \lambda_j \mathcal{L}_j, \sum_{j=1}^{4} \lambda_j = 1 \tag{5}$$

Here, $\mathcal{L}_j$ represents the loss term of the jth sub-task, and λ_j represents the corresponding task weight. Based on the above problem description, this paper extends the traditional single-point analysis of the supply chain decision support process to a state-aware and result-output process oriented towards multi-task collaboration, enabling the model to not only grasp the overall operation trend of the supply chain but also generate differentiated decision results for specific business scenarios, providing a clear problem basis for the design of subsequent deep learning-driven decision support methods.

3 Supply Chain Multi-source Data Fusion and Decision Support Method Based on Deep Learning

3.1 Construction of Multi-source Heterogeneous Data Fusion Model

In response to the problems of scattered data sources, significant structural differences, inconsistent time granularity, and complex inter-node relationships in supply chain data, this paper constructs a multi-source heterogeneous data fusion model oriented towards business scenarios. This model does not simply concatenate the procurement, production, inventory, logistics, sales, and external environment information as in the previous methods, but completes feature extraction and unified representation in stages following the "single-source encoding - cross-source alignment - dynamic fusion - state representation" approach. The overall structure of the multi-source heterogeneous data fusion model is shown in Figure 2, and the core module configuration is presented in Table 1.

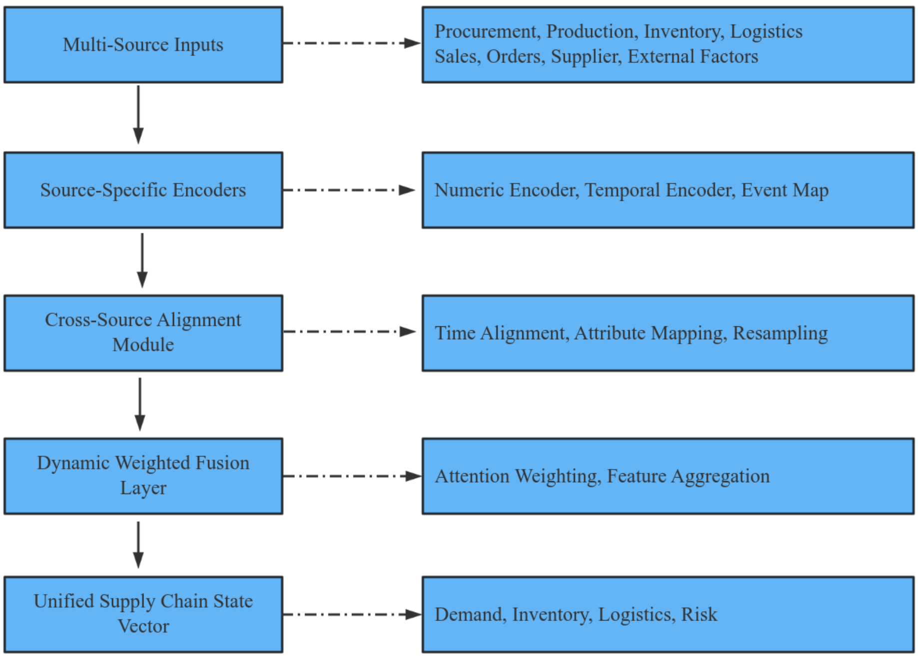

Figure 2: Structure diagram of multi-source heterogeneous data fusion model

Table 1: Configuration of core modules of multi-source heterogeneous data fusion model

Module Name	Primary Input	Output Dimension	Core Function	Parameter Settings
Single-source Feature Encoding Module	Original features such as procurement, inventory, and sales	64	Extract local semantic information of each source	2 fully connected layers
Temporal Feature Encoding Module	Logistics trajectory, order sequence	128	Capture time-dependent relationship	128 GRU hidden layer
Attribute Mapping Module	Heterogeneous encoding results	64	Complete dimension unification and attribute alignment	Mapping matrix Ak
Dynamic Weight Fusion Module	Aligned multi-source vectors	128	Adaptive allocation of source weights	4 Attention heads
State Representation Output Module	Sequence of fused vectors	128	Generate unified scene state representation	12 time window length

(1) Single-source feature encoding

Different sources of data have differences in statistical attributes and expression methods. Procurement, inventory, and sales data are mainly structured numerical data, logistics data have obvious temporal characteristics, and external environment data have both continuous variables and discrete event attributes. To retain the original semantics of each data source, this paper first establishes independent encoders for each type of input, mapping the original input $x_t^{(k)}$ to a low-dimensional embedding vector $z_t^{(k)}$. Its expression is:

$$z_t^{(k)} = \phi_k(x_t^{(k)}) = g(W_k x_t^{(k)} + b_k) \tag{6}$$

where, $\phi_k(\cdot)$ represents the encoding function of the kth data source, W_k and b_k represent the weight matrix and bias term respectively, and $g(\cdot)$ is a nonlinear activation function. Through this step, the multi-source original features can be uniformly mapped to a learnable space, providing a basis for subsequent cross-source fusion.

(2) Cross-source temporal alignment and attribute mapping

Since different data sources have different update frequencies, if the data is directly input into the model, it is easy to cause information misalignment. Therefore, this paper uses a unified time window T as the benchmark, resamples and aggregates daily, hourly, and event-level data, and completes dimension alignment through the attribute mapping matrix. Let the aligned input sequence be $\bar{z}_t^k$, then:

$$\bar{z}_t^k = A_k z_t^{(k)} \tag{7}$$

Among them, A_k is the attribute mapping matrix for the k-th type of data. This process ensures consistency in the time scale and representation dimension of features from different sources, reducing noise interference caused by direct interaction of heterogeneous data.

(3) Dynamic Weight Fusion Mechanism

The dependency of different operational stages of the supply chain on data sources varies. For example, during the demand fluctuation stage, sales and order information are more focused on, while during the fulfillment stage, logistics and inventory status are more relied upon. Therefore, this paper introduces a dynamic weight mechanism to adaptively allocate the importance of each data source based on the current scene state. The fusion is expressed as:

$$\alpha_t^{(k)} = \frac{\exp(\, q^\top \bar{z}_t^{(k)})}{\sum_{j=1}^{K} \exp(\, q^\top \bar{z}_t^{(j)})} \tag{8}$$

$$h_t = \sum_{k=1}^{K} \alpha_t^{(k)}\, \bar{z}_t^{(k)} \tag{9}$$

Here, $\alpha_t^{(k)}$ represents the weight of the k-th type of data source at time t, q is a trainable query vector, and h_t is the fused supply chain scenario state vector. This weight will be dynamically adjusted according to the changes in the scene status. During the stage of demand fluctuations, it will give more emphasis to front-end signals such as sales and orders. During the execution stage of delivery, it will accordingly enhance the role of operational information such as inventory and logistics, thereby better reflecting the shift of information focus in different stages of the supply chain and enhancing the model's ability to respond to changes in business scenarios.

(4) Global State Representation Output:

After obtaining the fused vector ht, this paper further adds the context modeling unit of the previous and subsequent states to extract global correlated features across time windows, forming a unified state representation H_t^* for subsequent decision support. Its expression is:

$$H_t^* = \psi(h_{t-n}, h_{t-n+1}, \dots, h_t) \tag{10}$$

Among them, $\psi(\cdot)$ represents the temporal aggregation function. The final output of H_t^* comprehensively reflects the demand changes, inventory pressure, logistics response and external disturbance status of the supply chain in the current period, and can be directly used as the input for the subsequent multi-task decision support module.

3.2 Design of Supply Chain Decision Support Method Driven by Deep Learning

After completing the fusion of multi-source heterogeneous data, this paper further builds a deep learning-driven decision support method for the supply chain business scenarios. Different from the traditional approach that only outputs a single prediction value, this paper incorporates demand identification, inventory judgment, distribution response, and risk warning into a unified decision-making framework. Based on the shared state representation, through task-adaptive branching, confidence evaluation, and recommendation generation mechanisms, it extends from "state perception" to "decision support". This method retains the modeling ability of deep learning for complex relationships and enhances the business usability of the output results. The core task module configuration is shown in Table 2.

Table 2: Configuration of Deep Learning-driven Supply Chain Decision Support Task Modules

Task Module	Primary Input Feature Dimensions	Output Class Number	Shared Representation Dimensions	Task Weight ω_m	Confidence Threshold τ_m	Primary Function	Application Goal
Demand Identification Module	96	4	128	0.28	0.80	Identify demand rising, stable, fluctuating, and falling states	Support procurement planning and stock preparation
Inventory Judgment Module	88	4	128	0.27	0.78	Judge inventory sufficient, normal, tight, and shortage states	Support inventory management and replenishment decisions
Distribution Response Module	104	3	128	0.23	0.82	Output high-priority, regular, and delayed response suggestions	Support logistics scheduling and fulfillment management
Risk Warning Module	92	4	128	0.22	0.85	Identify low-risk, general risk, high-risk, and high-risk states	Support abnormal warning and risk prevention

(1) Construction of Shared Decision Representation

Based on the unified supply chain state vector Ht* obtained previously, which integrates multi-source information such as procurement, production, inventory, logistics, sales, and external environment, if directly used for output of different tasks, it is prone to problems such as information competition and insufficient expression among tasks. Therefore, this paper first constructs a shared decision representation layer to further compress and map the fused state, obtaining the decision semantic vector st. It is expressed as:

$$s_t = \varphi(H_t^*) = \delta(W_s H_t^* + b_s) \tag{11}$$

where W_s and b_s represent the shared mapping matrix and bias term, and $\delta(\cdot)$ represents the nonlinear activation function. This vector comprehensively represents the overall operational state of the supply chain at the current moment, providing a unified input for subsequent multi-task decision branches.

(2) Design of Task Adaptive Gate-Controlled Branching

The information focus of different decision-making tasks in the supply chain is not consistent. Demand identification is more dependent on sales and order fluctuations, inventory judgment pays more attention to inventory levels and replenishment cycles, distribution response emphasizes logistics status and delivery timeliness, and risk warning is more sensitive to supplier anomalies and external disturbances. Although the shared representation can depict the overall operation status of the supply chain at the current moment, it still contains mixed information for different tasks. If directly input into each task branch, it is prone to cause a shift in the focus and interference from irrelevant features. Therefore, this paper builds adaptive gated units for each type of task, which automatically filter out the features that are more valuable for the current task based on the shared representation. The gated vector of the m-th task is expressed as:

$$g_t^{(m)} = \sigma(W_g^{(m)} s_t + b_g^{(m)}) \tag{12}$$

The corresponding task feature representation is:

$$u_t^{(m)} = g_t^{(m)} \odot s_t \tag{13}$$

Here, $\sigma(\cdot)$ represents the Sigmoid function, and $\odot$ represents element-wise multiplication. This design can prevent all tasks from sharing exactly the same feature representation, thereby enhancing the model's adaptability to differentiated business goals.

(3) Multi-task collaborative output mechanism

After obtaining the task features $u_t^{(m)}$, this paper sets four output heads for demand, inventory, distribution, and risk, forming a multi-task collaborative decision-making structure. The prediction results of each task are expressed as:

$$\hat{y}_t^{(m)} = \mathrm{softmax}(W_o^{(m)} u_t^{(m)} + b_o^{(m)}) \tag{14}$$

Among them, $\hat{y}_t^{(m)}$ represents the output probability distribution of the m-th task. Considering that the convergence speed and importance of different tasks vary during the multi-task training process, this paper adopts a dynamic weighted loss function:

$$\mathcal{L} = \sum_{m=1}^{4} \omega_m \mathcal{L}_m, \quad \sum_{m=1}^{4} \omega_m = 1 \tag{15}$$

Here, $\mathcal{L}_m$ represents the loss term of the corresponding task, and ω_m represents the task weight. Through this mechanism, the model can balance the contributions of different tasks during the overall learning process and improve the joint decision-making effect.

(4) Confidence assessment and recommendation generation

To enhance the interpretability and practical application value of the decision-making results, this paper calculates the corresponding confidence levels while outputting the task results, and combines them with the business rule templates to form decision recommendations that can directly be applied to management scenarios. The business rule templates here do not replace the model's judgment, but rather conduct further business-oriented interpretation of the prediction results based on factors such as response priority classification, risk level indication, and trigger conditions for manual review. The confidence level of the m-th task is defined as:

$$c_t^{(m)} = \max(\hat{y}_t^{(m)}) \tag{16}$$

When $c_t^{(m)}$ is higher than the preset threshold τ_m, the system directly outputs a highly reliable recommendation; when it is lower than the threshold, the cautious prompt mechanism is triggered, marking the result as "requiring manual review" or "the recommendation should be confirmed again based on upstream and downstream information". This "model output + confidence constraint" design enables this method not only to provide classification or prediction results, but to further form a risk-aware decision support output, which is more in line with the application requirements in supply chain management.

In summary, the decision support method constructed in this paper no longer remains at a single prediction task, but forms a deep learning decision support mechanism for multiple scenarios in the supply chain through shared representation, gated branches, multi-task collaboration and confidence constraint. This method can output more targeted, usable and interpretable decision results in complex and variable supply chain environments, providing a methodological basis for subsequent experimental verification.

4 Experimental Results and Analysis

4.1 Experimental Setup and Evaluation Metrics

To verify the effectiveness of the proposed method in supply chain multi-source data fusion and decision support, this paper constructs a multi-source heterogeneous experimental data set containing procurement, production, inventory, logistics, sales and external environment information. After comprehensive time window segmentation, abnormal sample elimination and missing value completion, a total of 12,000 valid samples were obtained, among which the training set, validation set and test set were 8,400, 1,200 and 2,400 respectively, with a ratio of 7:1:2. The model was trained in the PyTorch environment, using the Adam optimizer for parameter update, with an initial learning rate of 0.001, a batch size of 64, 100 training rounds and a hidden layer dimension of 128. Considering the construction of a joint decision model for the four tasks of demand recognition, inventory judgment, distribution response and risk warning, the evaluation metrics selected are accuracy, precision, recall and F1 value, and the results of the four tasks were statistically averaged using the macro-average method to comprehensively evaluate the model performance from overall correctness, positive class recognition ability and result balanceability aspects.

The formula for calculating accuracy is:

$$\mathrm{Acc} = \frac{\mathrm{TP} + \mathrm{TN}}{\mathrm{TP} + \mathrm{TN} + \mathrm{FP} + \mathrm{FN}} \tag{17}$$

The formula for calculating the accuracy rate is:

$$\mathrm{Precision} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FP}} \tag{18}$$

The formula for calculating recall rate is:

$$\mathrm{Recall} = \frac{\mathrm{TP}}{\mathrm{TP} + \mathrm{FN}} \tag{19}$$

The formula for calculating the F1 value is:

$$\mathrm{F1} = \frac{2 \times \mathrm{Precision} \times \mathrm{Recall}}{\mathrm{Precision} + \mathrm{Recall}} \tag{20}$$

Among them, TP, TN, FP, and FN represent true positive, true negative, false positive, and false negative respectively. These indicators can comprehensively reflect the classification performance of the model in the multi-task decision-making scenario of the supply chain, providing a unified evaluation basis for the subsequent experimental results analysis.

4.2 Result Analysis and Discussion

(1) Overall Performance Comparison Analysis

To verify the comprehensive performance of the proposed method in the multi-task decision-making scenario of the supply chain, this paper compares it with RF, LSTM, GRU, and Transformer models, and the results are shown in Table 3.

Table 3: Comparison of Experimental Results of Different Models

Model	Accuracy/%	Precision/%	Recall/%	F1/%
RF	84.7	83.9	85.1	84.5
LSTM	87.3	86.5	88.0	87.2
GRU	88.6	87.8	89.1	88.4
Transformer	90.3	89.4	90.7	89.7

It can be seen that the method proposed in this paper achieves the best results in all indicators. The accuracy rate is 92.8%, the precision rate is 91.9%, the recall rate is 93.4%, and the F1 value is 92.6%. It should be noted that the results in Table 3 are calculated using the macro-average statistical method for the four types of task indicators: demand identification, inventory judgment, distribution response, and risk warning. Therefore, the above values reflect the overall performance of the model in the multi-task combined scenario, rather than the local results of a single task. Compared with the best-performing comparison model Transformer, the accuracy rate has increased by 2.5 percentage points, and the F1 value has increased by 2.9 percentage points, indicating that the multi-source fusion and multi-task decision-making mechanism can more effectively enhance the ability to identify supply chain status.

(2) Model Convergence Process Analysis

To further examine the stability of model training, this paper draws a line graph of the change in training loss, as shown in Figure 3.

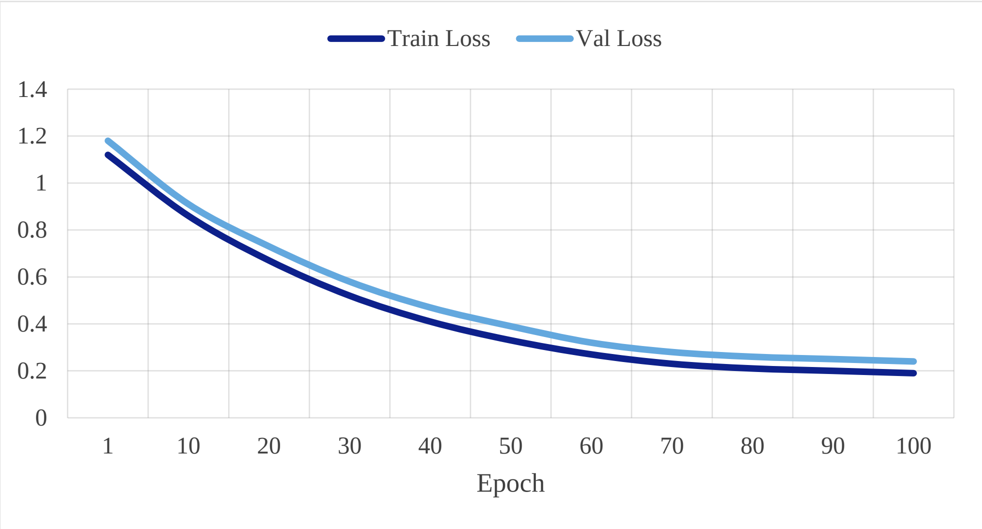

Figure 3: Line chart of training rounds and loss changes

As shown in Figure 3, as the number of training rounds increases, the model loss value continues to decrease and stabilizes after the 70th round, indicating that the model has good convergence characteristics. The training loss decreased from the initial 1.12 to 0.19, and the validation loss decreased from 1.18 to 0.24. The two curves show a basically consistent trend of change, indicating that the method in this paper did not show significant oscillations during the training process and has good generalization ability overall.

(3) Threshold Sensitivity and Decision Reliability Analysis

To investigate the impact of the confidence threshold setting on the decision output, this paper further drew the accuracy-recall rate change curve, as shown in Figure 4.

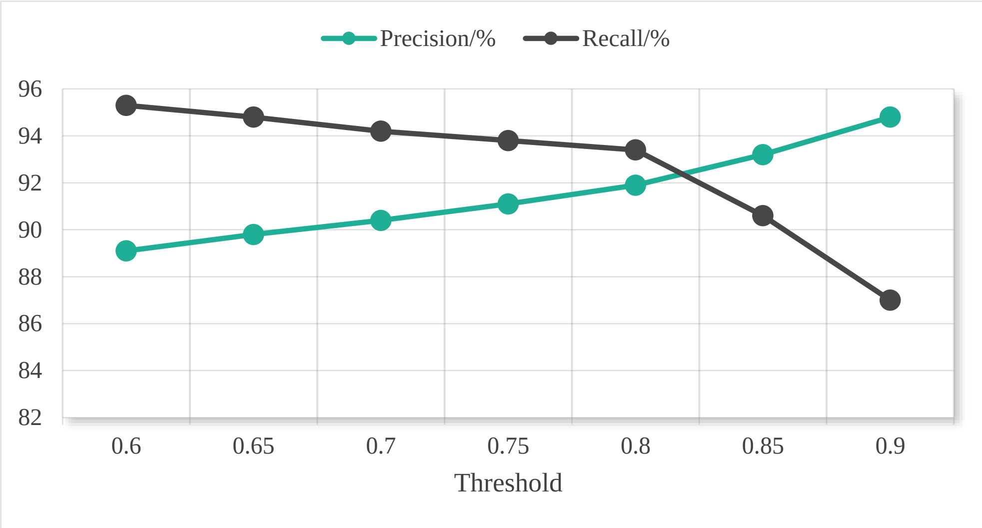

Figure 4: Curve chart of precision and recall rates under different confidence threshold values

As the threshold increased from 0.60 to 0.90, the model's accuracy rate rose from 89.1% to 94.8%, while the recall rate dropped from 95.3% to 87.0%. When the threshold was set at 0.80, the accuracy rate and recall rate reached 91.9% and 93.4% respectively, with the corresponding F1 value reaching the highest at 92.6%. This indicates that under the current experimental settings of this study, a threshold of 0.80 shows a better balance between the reliability of the results and the coverage of the task, and also demonstrates that the designed confidence constraint mechanism can well adapt to the precision and coverage requirements in the supply chain decision support scenarios.

5 Conclusion

This paper addresses the challenges of integrating multi-source heterogeneous data in the supply chain and the difficulty of a single-task model in supporting complex business decisions. It constructs a research framework that connects data system modeling, multi-source fusion, and multi-task decision output. Through single-source encoding, attribute mapping, dynamic weight fusion, and global state representation, the model achieves unified expression of multi-source information; through shared representation, gated branches, dynamic weighted loss, and confidence evaluation, a decision support mechanism for demand, inventory, distribution, and risk is formed. Experimental results show that the method achieves an accuracy of 92.8% and an F1 value of 92.6% on 12,000 samples, with the training loss reduced from 1.12 to 0.19 and the validation loss from 1.18 to 0.24. This indicates that the method has good convergence and stability under the current constructed dataset and offline training and validation conditions, and can provide effective support for multi-scenario supply chain decisions. At the same time, this paper's verification is mainly based on existing samples and offline experimental environments, and its applicability in real-time streaming data, cross-enterprise collaboration, and more complex network structures still has further testing space. In the future, it can further combine graph neural networks, real-time streaming data, and cross-enterprise collaboration scenarios to improve the online decision-making ability and generalization level of the model.

About the Author

Xiang Ji was born in Lu’an, Anhui. China, in 2002. He obtained a bachelor's degree from Southeast University in China. He obtained a Master’s degree from City University of Hong Kong.His main research direction is Operation and Supply Chain management.

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