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Optimization and Benefit Assessment of Production Supply Chain Networks Using Graph Neural Network Models

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With the flourishing development of global economy, effective management of production supply chains is crucial for the competitiveness of enterprises. Optimizing supply chain networks can not only improve the efficiency of resource allocation but also enhance market responsiveness and systemic risk resistance. Traditional supply chain network optimization methods, focusing mostly on linear models and static analysis, fall short in addressing the growing complexity and dynamism. The emergence of Graph Neural Network (GNN) models in recent years has offered new opportunities to tackle non-linearity and structural dynamism in supply chain networks. However, existing research still faces methodological limitations in supply chain node relationship mining and benefit assessment. This study introduces an optimization and benefit assessment method for production supply chain networks based on GNNs. Firstly, by developing a node role type-aware graph neural network model, this paper achieves in-depth mining and optimization of node relationships within production supply chain networks. Secondly, a hierarchical factor analysis method is used to comprehensively assess the benefits of the production supply chain. This method can dynamically capture changes in node roles and relationships within the supply chain network, optimize the network structure, and provides a multidimensional, multilevel framework for benefit assessment. This study not only expands the application of GNN in the field of supply chain management but also provides a new analytical tool for the comprehensive assessment of supply chain benefits.

ACM CCS (2012) Classification: Computing methodologies → Machine learning → Machine learning approaches → Neural networks

Keywords: supply chain network optimization, graph neural network (GNN), node role type awareness, hierarchical factor analysis, benefit assessment

1. Introduction

In the wave of globalization, the production supply chain, as the key link connecting producers and consumers, its operational efficiency and stability directly affect the competitiveness of enterprises and the speed of market response [1–3]. With the rapid development of information technology, especially the application of artificial intelligence and big data technologies, supply chain management has entered a new era [4, 5]. GNN, as a powerful data processing tool, can effectively handle the non-Euclidean structure data in supply chain networks, reveal the deep-level relationships and dynamic changes between nodes, providing new ideas and methods for the optimization of supply chain network structure [6–8].

The efficient configuration and management of supply chains are hot issues of common concern in both the academic and business communities [9, 10]. Among many research directions, how to use modern computational tools and algorithms to optimize the structure of the supply chain and improve its overall benefits is key to enhancing the competitiveness of the supply chain [11–13]. GNN models, with their natural advantages in processing graph-structured data, offer a new perspective for solving the problems of supply chain network structure optimization and benefit assessment, which has high research significance and application value [14, 15].

However, existing research methods still have certain defects and shortcomings when dealing with complex supply chain network structures. Traditional supply chain network analysis often relies on linear models, which tend to ignore the complex nonlinear relationships and dynamic changes between nodes within the supply chain system, leading to optimization results that do not fully reflect the actual operation of the supply chain [16–18]. In addition, existing methods often fail to fully consider the impact and role of factors at different levels of the supply chain when evaluating benefits, leaving room for improvement in the accuracy and reliability of evaluation results [19–21].

In the field of research on supply chain network structure optimization and performance evaluation, the latest advancements are primarily focused on how to use artificial intelligence and machine learning technologies, especially GNNs, to enhance the accuracy of predictions and the adaptability of networks. Researchers are exploring more complex network structures and algorithms, such as deep learning and reinforcement learning, to achieve real-time responses to dynamic changes in the supply chain. Additionally, the application of big data technology is increasingly prevalent, allowing insights to be drawn from a broader range of data sources, thereby optimizing the operation of the entire supply chain. Meanwhile, interdisciplinary approaches are emerging, such as integrating supply chain management with environmental sustainability, economic policies, and other areas to implement more comprehensive supply chain strategies.

This study proposes a new type of production supply chain network structure optimization and benefit assessment method based on GNNs, aimed at addressing the deficiencies in existing research. First, we designed a node role type-aware GNN model that can intelligently identify and optimize node relationships within the production supply chain network, enhancing the efficiency and robustness of the network structure. Second, by introducing hierarchical factor analysis, this study comprehensively assessed the multi-level benefits of the production supply chain, quantifying supply chain benefits from a more comprehensive and refined perspective. The methods of this study not only provide new theoretical and technical support for the optimization of the production supply chain network structure but also offer a new analytical framework for supply chain benefit assessment, with high theoretical significance and practical value.

2. Role-Aware Mining and Optimization of Node Relationship Structures in Production Supply Chain Networks

In modern supply chain management, quickly and accurately understanding and optimizing the complex structure of supply chain networks is key to improving overall efficiency and responding to market changes. This paper innovatively integrates deep cognition of node roles into the optimization of the supply chain network by constructing a production supply chain GNN based on node role type awareness. This method can precisely identify and optimize key nodes and their relationships within the network, thereby enhancing the efficiency and adaptability of the entire supply chain. Through the study of new methods for relationship linking, this paper not only addresses the deficiencies of traditional models in handling the dynamic complexity of supply chain networks but also provides enterprises with a new strategy to respond to constantly changing market demands and supply conditions in a more flexible and intelligent manner, with significant theoretical innovation and practical application value.

Specifically, the constructed production supply chain GNN based on node role type awareness includes four modules: the node feature construction module, the node role type embedding module, the node role type injection module, and the node relationship linking generation and optimization module. The following provides a detailed introduction to each module. In the proposed GNN model for supply chain network structure optimization based on node role type awareness, the relationships between various modules are closely integrated and highly synergistic. The node feature construction module first extracts key features from raw data, such as order volume, delivery time, production capacity, *etc.*, providing a data foundation for subsequent module inputs. Next, the node role type embedding module utilizes the powerful capabilities of GNN to identify the roles of different nodes based on the extracted features and generates role embedding vectors, which help capture the core functions and relationships of nodes in the supply chain. The node role type injection module then infuses this role information into the network, enhancing the model's understanding and prediction of different node behaviors. Finally, the node relationship link generation and optimization module uses the outputs from the previous modules to optimize the connections between nodes, such as strengthening links between nodes with high cooperation efficiency and weakening links with low efficiency, thereby overall enhancing the performance and robustness of the supply chain network. Figure 1 presents a schematic diagram of the model structure.

2.1. Node Feature Construction Module

The node feature construction module is the foundation of the GNN, whose primary function is to extract feature vectors from complex supply chain data that can represent the state and attributes of each node. In the production supply chain, this specifically includes multi-dimensional information such as the quality of raw materials, the delivery cycle of suppliers, and the performance of production equipment. Through this module, seemingly scattered and unstructured data can be transformed into structured feature representations, thereby providing accurate input for subsequent analysis and optimization.

Given the extremely diverse types and sources of data in the supply chain environment, including but not limited to transaction records, logistics information, production data, *etc.*, the structural feature of the node feature construction module needs to be capable of processing and integrating multi-source heterogeneous data to form a comprehensive node feature representation, so a highly flexible data processing framework is required to convert these pieces of information into fixed-length vectors. This paper chooses to randomly initialize the node embedding matrix and the relationship embedding matrix of the constructed GNN. Assuming the network node relationship set is represented by R_1, the node set by R_2, and the embedding dimension of nodes and relationships by f_x, then the node feature matrix and relationship feature matrix can be represented by L_R and L_E, satisfying $L_E \in R_1^{|R_1| \times f_x}$, and $L_R \in R_2^{|R_2| \times f_x}$.

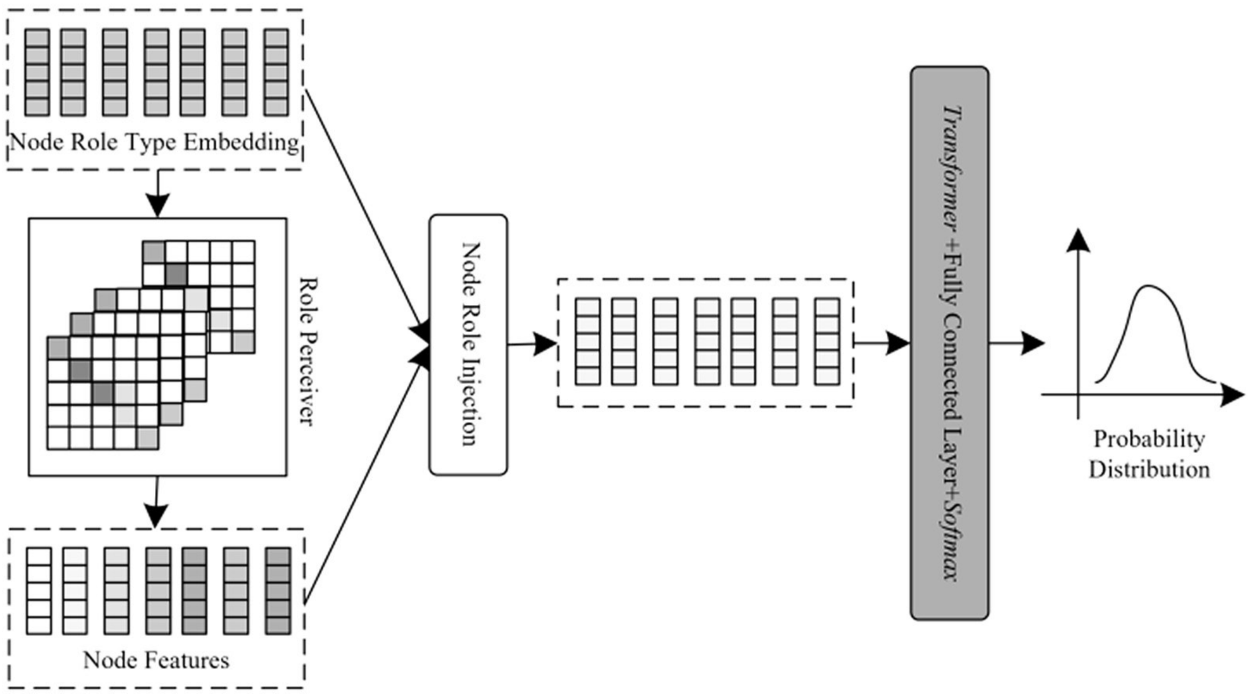

Figure 1. Schematic diagram of the model structure.

2.2. Node Role Type Embedding Module

The purpose of the node role type embedding module is to identify and categorize the roles and functions of different nodes within the supply chain. In the supply chain network, different nodes play different roles, such as suppliers, manufacturers, distributors, *etc.*, and each role has different functions and influences within the entire network. This module can capture and embed this type information of roles by learning the feature representations of nodes, thereby providing a basis for more precise network analysis and structure optimization.

The structural feature of the node role type embedding module is reflected in its deep learning capability for node roles. This module includes a trained role perceiver that can determine the roles of nodes in the supply chain based on their feature representations. Assuming the embedding dimension is represented by f_x, and the number of potential role types by M, then the role perceiver is represented by $Q_y \in R_1{}^{f_x \times f_x \times M}$. The role perceiver represents this role type information in the form of embedding vectors, making each node's role feature comparable and quantifiable.

Specifically, for a b-ary relational fact $FA = ((g, e, y; s_u, c_u), u = 1, 2, ..., l$, consider calculating the supply chain role type embedding for a parent node g as an example. By querying the node feature matrix L_R, we can obtain the embedding G of g, and by querying the relationship feature matrix L_E, we can obtain the embedding E of the main relationship e. The role perceiver can perceive up to M types of roles. The detailed steps for embedding the role type that g plays under the condition of e are elaborated as follows:

1. Assuming the entity role perceiver is represented by Q_y, the following formula gives the similarity score calculation between g and various role types under the condition of e:

$$g_{SC} = \text{softmax}(g^Y Q_y e) \tag{1}$$

2. Further, based on the following formula, find the subscript of the most similar role type:

$$g_{IN} = MAX(g_{SC}) \tag{2}$$

   Let $g_{IN} \in R^M$, through the above formula, the highest score for various role types in g_{SC} is set to 1, and the remaining scores are set to 0.

3. Querying the role perceiver with g_{IN} obtains the diagonal matrix q, *i.e.*, the role type corresponding to g:

$$q = Q_y \, g_{IN} \tag{3}$$

4. The parent node role embedding $ROLE_g$ can be obtained by acquiring the diagonal element values of q, with the calculation method as follows:

$$ROLE_g = diag(q) \tag{4}$$

The calculation methods for the supply chain parent node and the supply chain root node are the same, both obtained through Q_y under the condition of the main relationship.

2.3. Node Role Type Injection Module

The node role type injection module integrates the role information learned from the node role type embedding module into the GNN to enhance the model's understanding of the supply chain network structure. Through this injection mechanism, the model not only recognizes the features of each node but also understands the specific function and role of each node within the network. This step is key to targeted optimization, enabling the model to adjust the relationships and processes between nodes based on their role types to optimize the overall network performance and stability. For example, for critical manufacturing nodes, the model would strengthen their connections with key suppliers to ensure the stability of material supply.

The structural feature of the node role type injection module lies in its ability to effectively integrate role type information with node features. This often involves complex feature fusion techniques to ensure that role type information is effectively integrated into the node representation without disrupting the original node feature structure. By finely adjusting the weight and presentation of role information, this module ensures the importance of role types within the overall feature representation, thereby guiding the GNN to consider node role differences when processing node interactions. In the process of effectively integrating role type information with node features, this paper adopts two fusion methods: Point-wise addition and Concatenate, the principles of which are shown in Figures 2 and 3.

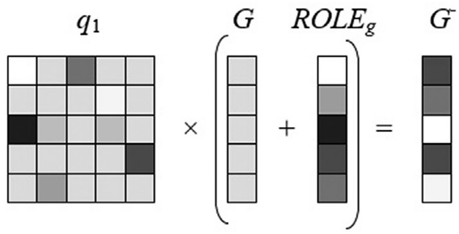

Figure 2. Principle of the Point-wise Addition Method.

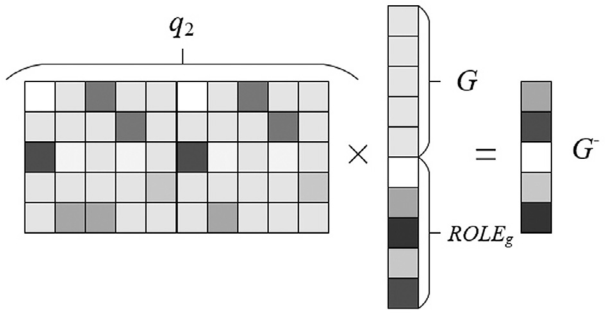

Figure 3. Principle of the Concatenate Method.

1. Point-wise addition method: Assuming the parameter matrix learned by the model is represented by $q_1 \in E^{f_x \times f_x}$, the feature representation of the entity after role information injection, $\bar{g}$, is obtained by adding g and $ROLE_g$ point-wise, followed by a linear transformation.

$$\bar{g} = q_1(g + ROLE_g) \tag{5}$$

2. Concatenate method: Assuming the parameter matrix for linear transformation after vector concatenation by the model is represented by $q_2 \in E^{f_x \times f_x}$. When the entity feature and role feature are concatenated by $[g; ROLE_g]$, then the calculation formula is:

$$\bar{g} = q_2 \lfloor g; ROLE_g \rfloor \tag{6}$$

2.4. Node Relationship Linking Generation and Optimization Module

Finally, the node relationship linking generation and optimization module serves as the decision-making center of the entire GNN, primarily functioning based on the outputs of the first three modules. It is responsible not only for generating optimal links between nodes but also for continuously adjusting and optimizing these links to adapt to changes in the supply chain environment. Through this module, the entire supply chain network can be reconfigured to make resource flow more efficient while reducing potential risks and bottlenecks. For example, the module may discover and reduce excessive connections between non-critical nodes or adjust the connection strategy with other nodes in advance if it predicts that a particular node will encounter problems, thereby enhancing the robustness and adaptability of the entire supply chain.

The node relationship linking generation and optimization module needs to be capable of dynamically constructing and adjusting relationships between nodes. This module employs a Transformer module to learn the optimal connection patterns between nodes on a global scale. By continuously assessing network performance metrics, such as process efficiency and risk levels, it can identify and implement necessary link adjustments, such as strengthening connections between key nodes or weakening unnecessary connections, to achieve real-time optimization and adaptability adjustments of the supply chain network.

Specifically, let a b-ary relational fact be represented by $FA = (g, e, y; s_u, c_u)$, $u = 1, ..., l$, and its embedding by $FA^* = (G, E, Y; S_u, C_u)$, $u = 1, ..., l$. After querying the node feature matrix and the relationship feature matrix, we obtain $FA^* = (G, E, Y; S_u, C_u)$, $u = 1, ..., l$, where missing nodes can be replaced by $[MA]$ nodes. Injecting entity feature representations into supply chain role features yields $\overline{FA} = (\bar{g}, \bar{e}, \bar{y}; \bar{s}_u, \bar{c}_u)$, $u = 1, ..., l$. The *Transformer* captures interactions between nodes within the b-ary node relationship, then outputs a sequence of hidden state vectors for the nodes in the b-ary relational fact $((z_1, z_2, ..., z_j), j = 1, ..., 2l + 3$. Let the hidden states of nodes masked with $[MA]$ nodes be represented by Z_{MA}. After processing through a *softmax* layer, the probability distribution o of missing nodes in the node set is output, with the node having the highest probability value selected as the predicted result for the missing node in the node relationship linking process.

Assuming the probability value for the missing node being the y-th node in the prediction result vector o is represented by o_y, and the value of the y-th entry for label t is represented by t_y. The following formula provides the expression for the loss function required for model training:

$$LOSS = \sum_{y} t_y \log o_y \tag{7}$$

In the method proposed in this paper, the key technologies include the node feature construction module and the node role type embedding module. The node feature construction module is responsible for extracting feature information of nodes from the production supply chain network. This feature information can include historical performance data of the nodes, attributes of the nodes, and relationship information among the nodes. The node role type embedding module is the core part of our designed GNN model. It learns the relationships between nodes and embeds the nodes into a high-dimensional vector space for subsequent network optimization and performance evaluation. The design and implementation of these two modules are among the key technologies of our method. They effectively extract and learn information from the production supply chain network and provide strong support for subsequent optimization and evaluation.

3. Hierarchical Factor Analysis for Benefit Assessment of the Production Supply Chain

Figure 4 presents the research route of this paper. In the study of production supply chain structure optimization, assessing the benefits of the supply chain is crucial, as this directly relates to core competitiveness indicators such as operational cost, service level, and market response speed. Through systematic benefit assessment, it is possible to accurately quantify performance improvements before and after supply chain optimization, identify value creation points and potential bottlenecks during the optimization process, thereby providing decision-makers with clear data support and directions for improvement. This not only helps to enhance the efficiency of resource allocation and reduce operational risks, but also ensures that the supply chain can respond more agilely to market changes, enhancing the entire system's sustainability and competitiveness. In this study, the hierarchical factor analysis method is implemented through the following steps to achieve a comprehensive assessment of supply chain performance: First, define multiple hierarchical factors for evaluation, such as cost efficiency, delivery speed, and supply chain stability. Then, set evaluation indicators for each factor and collect corresponding data. Next, use statistical or machine learning methods to conduct quantitative analysis of each hierarchical factor, assessing the impact and contribution of each indicator. This process may include methods such as factor analysis and principal component analysis to extract the main influencing factors. Finally, synthesize the analysis results from all levels to form a quantitative assessment of the overall supply chain performance.

Figure 4 outlines the research route of this paper. Hierarchical factor analysis is capable of revealing key influencing factors within the supply chain and their interactions across multiple levels. This method is suitable for dealing with variable relationships and the multidimensionality of data in complex systems. By decomposing layer by layer, from macro to micro, it identifies and quantifies the various factors affecting the supply chain's benefits. This approach not only allows for a comprehensive assessment of the supply chain's overall performance but also delves into the specific contributions and optimization spaces at each level. For this reason, this paper opts to employ hierarchical factor analysis to assess the benefits of the production supply chain.

(1) Panel Data Standardization

In the assessment of supply chain benefits, collected data encompasses various segments from raw material procurement, production processes, inventory management to the final distribution of products. This data (Table 1) includes time series data, cross-sectional data, and mul-

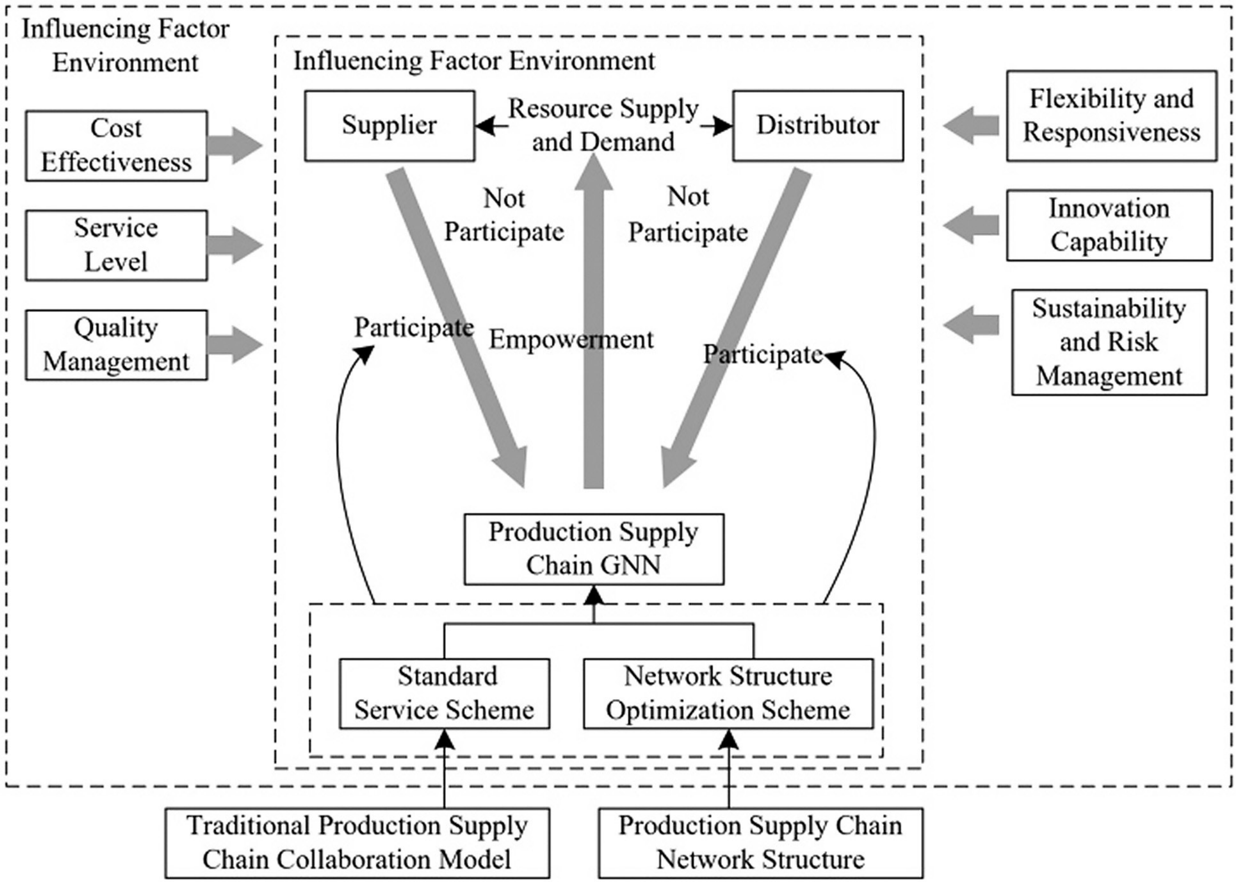

Figure 4. Research Route of This Paper.

Table 1. Cross-sectional data expansion table.

Time	**1**	**...**	***p***	**...**	***P***
Sample Indicator	$1...k...t$	...	$1...k...t$	...	$1...k...t$
Individual 1	$x_{11}(1)...x_{1k}(1)...x_{1t}(1)$	...	$x_{11}(t)...x_{1k}(t)...x_{1t}(t)$	...	$x_{11}(T)...x_{1k}(T)...x_{1t}(T)$
...	...	...	...	...	...
Individual u	$x_{u1}(1)...x_{uj}(1)...x_{ut}(1)$	...	$x_{u1}(t)...x_{uj}(t)...x_{ut}(t)$	...	$x_{u1}(T)...x_{uj}(T)...x_{ut}(T)$
...	...	...	...	...	...
Individual b	$x_{b1}(1)...x_{bj}(1)...x_{bt}(1)$	...	$x_{b1}(t)...x_{bj}(t)...x_{bt}(t)$	...	$x_{b1}(T)...x_{bj}(T)...x_{bt}(T)$

tidimensional indicators such as delivery time, cost, quality, customer feedback, *etc.* The purpose of panel data standardization is to eliminate biases caused by different units of measurement or ranges of values, ensuring the effectiveness of subsequent analyses. This is achieved through *z-score* normalization, which transforms the values of each variable into a dimensionless form and aligns them on the same scale. The formula for standardization is:

$$X_u = \frac{z_u - R(z_u)}{\sqrt{VAR(z_u)}}, u = 1, 2, ..., b \tag{8}$$

(2) Cross-Sectional Data Suitability Test

To ensure the accuracy of factor analysis, it is essential to test the suitability of the collected cross-sectional data. This step mainly includes the Kaiser-Meyer-Olkin (*KMO*) test and Bartlett's test of sphericity. A high *KMO* value (greater than 0.6) indicates that the variables in the sample are suitable for factor analysis. Bartlett's test is used to check if there is a correlation between variables, with a p-value less than a significance level (*e.g.*, 0.05) rejecting the null hypothesis of no correlation among variables, suggesting that the data is suitable for factor analysis.

(3) Extraction of Common Factors

To identify and quantify the latent dimensions affecting the benefits within the supply chain, it is necessary to extract common factors. Through the method of principal component analysis, several unobservable common factors can be extracted from multiple related observational indicators. These factors represent the core dimensions of supply chain benefits, such as cost control, delivery efficiency, service quality, and flexibility, *etc.* This step involves deciding the number of factors to extract, usually based on the criterion of eigenvalues greater than 1 or the percentage of total variance explained cumulatively. The extracted factors help understand which elements significantly impact benefits within the supply chain, providing a quantitative basis for subsequent optimization of the supply chain structure.

(4) Rotation of the Factor Loading Matrix

After extracting the common factors affecting supply chain benefits, factor loading matrix rotation simplifies each factor's interpretation of the variables. Through orthogonal rotation (*e.g.*, Varimax rotation) or oblique rotation (*e.g.*, Oblimin rotation), each factor has higher loadings on some variables and lower on others, making each factor more easily interpreted as an independent and clearly defined dimension. For example, one factor might distinctly represent the "response speed" of the supply chain, while another represents "cost control". This helps identify the factors that most significantly affect supply chain benefits and provides direction for optimizing these factors.

(5) Determination of Factor Scores Formula and Calculation of Composite Scores

After determining factor loadings, the next step is to calculate each factor's score. This typically involves weighting each observational variable by its loading on the factor, then combining these weighted scores to calculate each factor's score. The composite score is obtained by integrating all significant factors' scores, usually through a weighted average, to assess the overall benefits of the supply chain. In supply chain structure optimization, this composite score can serve as a key indicator to help decision-makers understand the trend of supply chain benefits under different optimization schemes, thus supporting the formulation of more scientific and rational optimization decisions. Assuming the scores of each common factor are represented by D_u, the coefficients of each indicator value for the u-th common factor in the component score coefficient matrix are represented by S_u, and the standardized values of each indicator in the u-th common factor are represented by X_u. The formula for calculating each common factor's score is as follows:

$$D_u = \sum S_u X_u \tag{9}$$

Assuming the composite score is represented by D, the score of the u-th common factor by D_u, the variance contribution rate of the u-th common factor after rotation by α_u, and the weight of the u-th common factor by $\alpha_u/\sum\alpha_u$, the formula for calculating the composite score is as follows:

$$D = \sum\left(\frac{\alpha_u}{\sum\alpha_u}\right)D_u \tag{10}$$

(6) Factor Analysis and Cluster Analysis of Panel Data

Finally, by conducting factor analysis on panel data, it is possible to understand the trends in supply chain benefits at different time points, identify key factors affecting benefit fluctuations, and assess the stability of these factors over time. Additionally, through cluster analysis, supply chains can be grouped according to benefit characteristics, identifying configurations or patterns with similar performances. For example, it might identify a group of supply chains that are efficient and low-cost or another group that offers high service quality but at a higher cost. This analysis helps reveal best practices and potential risk points, providing more targeted recommendations for optimizing the supply chain structure. Based on the evaluation vector for each cross-section, a comprehensive evaluation matrix can be formed as follows:

$$T = \begin{pmatrix} d_1(1) & \cdots & d_1(Y) \\ \vdots & \ddots & \vdots \\ d_b(1) & \cdots & d_b(Y) \end{pmatrix} \tag{11}$$

This paper applies the proposed GNN-based method for production supply chain network structure optimization and performance evaluation to a real-world manufacturing supply chain case. Specifically, a manufacturing company producing automotive parts was selected as the subject of study, cooperating with multiple suppliers and distributors. Data on production, procurement, and sales over the past year were collected, and a production supply chain network model was established. Initially, the supply chain network was optimized using our designed GNN model that is aware of node role types. By identifying and optimizing the relationships between different nodes, the efficiency and robustness of the supply chain network were improved. Subsequently, the introduced hierarchical factor analysis method was used to conduct a comprehensive assessment of the multi-level benefits of this supply chain, including costs, delivery time, and supply chain risks. The study found that after optimization using our method, the company's supply chain achieved significant improvements in cost control, delivery time, and risk management. Production efficiency increased, inventory costs decreased, delivery times were shortened, and the robustness of the supply chain was enhanced. This demonstrates the practical feasibility and effectiveness of the proposed method for optimizing the structure of production supply chain networks and evaluating their benefits.

4. Experimental Results and Analysis

Based on the experimental results in Table 2, we can analyze and compare the impact of different node role type injection methods on model performance. In Table 2, performance metrics such as *MRR* (Mean Reciprocal Rank), *hit@*1, *hit@*3, and *hit@*10 are used to measure the accuracy of the model's link prediction. *MRR* represents the average reciprocal rank of all queries, while *hit@*k indicates the proportion of actual links within the top k predictions made by the model. The column for "No Fusion" serves as a baseline, showing the model's performance without integrating node role type information. With an *MRR* of 0.512 and *hit@*1 of 0.412, the model demonstrates a certain predictive ability without considering node role types, indicating room for optimization.

For the Point-wise addition method, when node features and node role types are integrated using point-wise addition, all metrics improve. *MRR* increases from 0.512 to 0.528, and *hit@*1 increases from 0.412 to 0.457, with corresponding improvements in *hit@*3 and *hit@*10 as well. This suggests that the Point-wise addition method can effectively combine node features and node role type information, thereby enhancing the model's predictive capability.

The Concatenate method, which injects node role type information through concatenation, shows inconsistent characteristics. Although there is an improvement in *hit@*10 relative to the baseline, reaching 0.714 and indicating effectiveness in predicting higher-ranked links, there is a significant drop in *MRR* and *hit@*1, with *MRR* decreasing to 0.239. This indicates that the Concatenate method increases the number of model parameters or alters the feature space, leading to a decrease in performance when predicting the most relevant links.

Table 2. Experimental results of different node role type injection methods.

Model	***MRR***	***hit@*1**	***hit@3***	***hit@*10**
No Fusion	0.512	0.412	*0.548*	0.652
Point-wise addition Method	0.528	0.457	0.563	0.687
Concatenate Method	0.239	0.446	0.568	0.714

In conclusion, the Point-wise addition method is an effective way to integrate role type information in the GNN model designed in this paper based on node role type awareness. It not only outperforms the baseline without fusion in all metrics but also shows better performance in MRR and *hit@*1 compared to the Concatenate method. These two metrics are particularly crucial for assessing the model's accuracy in predicting the most relevant links. Therefore, the Point-wise addition method is a more appropriate choice for optimizing node relationships in production supply chain networks, enhancing the efficiency and robustness of the network structure.

From the data in Tables 3–5, the following analysis can be conducted regarding the performance of different models for node relationship linking generation and optimization across Datasets 1, 2, and 3, which contain 33%, 66%, and 100% of node relationship linking facts, respectively.

From Table 3 (Dataset 1), it is observed that models using Transformer architecture (GATs, TCN, HGT, GTN) generally outperform those not using Transformer (Node2Vec, DeepWalk, SDNE, LINE) in terms of *MRR* and *hit@*1, *hit@*10 metrics. The model proposed in this paper, when employing Transformer, further improves performance, achieving the highest values in *MRR*, *hit@*1, and *hit@*10 among all models listed. This demonstrates the advantage of the Transformer module in capturing global connection patterns and the effectiveness of the proposed model in integrating these insights.

Table 4 (Dataset 2) shows that on a dataset containing more node relationship linking facts, the model presented in this paper surpasses other models across all metrics, regardless of whether Transformer is used or not. Notably, improvements in *MRR* (from 0.586 to 0.628) and *hit@*1 (from 0.536 to 0.559) indicate the model's high accuracy in predicting the most relevant links.

According to Table 5 (Dataset 3), the proposed model outperforms other models in almost all performance metrics. Especially, achieving an *MRR* of 0.639, a result better than any other model and obtained on the largest dataset, means that the model maintains its superior performance in more complex network settings.

Table 3. Experimental results of different models for node relationship linking generation and optimization on dataset 1.

Type	Model	*MRR*	*hit@*1	*hit@*10
Not Using *Transformer*	*Node2Vec*	0.168	0.128	0.257
	DeepWalk	0.234	0.167	0.365
	SDNE	0.278	0.212	0.412
	LINE	0.285	0.236	0.441
Using *Transformer*	*GATs*	0.336	0.265	0.465
	TCN	0.348	0.274	0.473
	HGT	0.344	0.254	0.475
	GTN	0.347	0.279	0.480
The Proposed Model		0.358	0.286	0.482

Table 4. Experimental results of different models for node relationship linking generation and optimization on dataset 2.

Type	Model	*MRR*	*MR*	*hit@1*	*hit@3*	*hit@10*
Not Using *Transformer*	*Node2Vec*	0.524	1358	0.448	0.539	0.625
	DeepWalk	0.248	1625	0.512	0.578	0.648
	SDNE	0.559	1598	0.517	0.579	0.653
	LINE	0.586	1248	0.536	0.612	0.689
Using *Transformer*	*GATs*	0.557	968	0.485	0.586	0.669
	TCN	0.563	1325	0.519	0.612	0.678
	HGT	0.534	762	0.485	0.578	0.652
	GTN	0.541	1625	0.483	0.579	0.652
The Proposed Model		0.628	1324	0.559	0.634	0.712

Table 5. Experimental results of different models for node relationship linking generation and optimization on dataset 3.

Type	Model	*MRR*	*MR*	*hit@1*	*hit@3*	*hit@10*
Not Using *Transformer*	*Node2Vec*	0.512	839	0.458	0.517	0.589
	DeepWalk	0.623	879	0.578	0.532	0.678
	SDNE	0.568	2215	0.541	0.589	0.612
	LINE	0.623	638	0.558	0.634	0.712
Using *Transformer*	*GATs*	0.638	652	0.578	0.647	0.725
	TCN	0.629	728	0.589	0.648	0.714
	HGT	0.624	648	0.548	0.652	0.716
	GTN	0.625	623	0.552	0.638	0.718
The Proposed Model		0.639	735	0.612	0.658	0.721

Across all three tables, it is evident that as the dataset includes more node relationship linking facts, the performance of the model presented in this paper also improves, indicating that the model adapts well to the richness and complexity of the data. The collaborative work of the node feature construction module, node role type embedding module, node role type injection module, and node relationship linking generation and optimization module enables effective prediction and optimization of node relationships under various conditions. Particularly, the node relationship linking generation and optimization module, leveraging the advantages of the Transformer architecture, seeks optimal connection patterns on a global scale, showcasing its efficiency and robustness in handling complex network structures.

Compared to traditional linear models, the GNN-based method proposed in this paper for production supply chain network structure optimization and performance evaluation has significant advantages. Traditional linear models often overlook the complex relationships between nodes in the production supply chain network, simplifying these relationships into linear or simple models. This simplification can prevent the model from fully capturing the true structure and complexity of the supply chain network, thus limiting the model's performance and predictive ability. In contrast, the proposed method uses a CNN model, which can more accurately identify and optimize the relationships between nodes in the production supply chain network, enhancing the efficiency and robustness of the network structure. Through the perception and embedding of node role types, the model can better understand and utilize the potential connections between nodes, thereby achieving a refined assessment and optimization of supply chain benefits.

Figure 5 shows the relationship between node stability and the probability of disruption risk, the proportion of efficiency improvement, and the proportion of resilience enhancement. Node stability changes from 0 to 1, representing the degree of stability enhancement in nodes of the production supply chain network after optimization measures are implemented. The reduction in the probability of disruption risk, along with increases in the proportion of efficiency improvement and resilience enhancement, are important indicators of supply chain network optimization. The figure illustrates that as node stability increases, the probability of disruption risk significantly decreases, from 0.98 to 0.09, indicating that implementing optimization measures within the network can greatly reduce the network's disruption risk due to node instability. This is a key factor in improving the robustness of the production supply chain. The proportion of efficiency improvement increases from 0.1 to 0.8, meaning that as the stability of network nodes improves, the overall operational efficiency of the supply chain network significantly increases. This is due to reduced reconfiguration time and costs caused by node failures, or because more stable nodes can process information and logistics more efficiently. The proportion of resilience enhancement also increases from 0.1 to 0.9, showing that the network's ability to return to normal operations after facing external shocks and internal failures is greatly enhanced. This indicates that the network can not only withstand risks but also quickly recover to an efficient state when risks occur. It can be concluded that the constructed model significantly enhances the network's stability by intelligently identifying and optimizing the relationships between nodes in the production supply chain network, thereby effectively reducing disruption risk, improving operational efficiency, and enhancing the network's resilience. Moreover, the application of hierarchical factor analysis to comprehensively assess the multi-level benefits of the supply chain further confirms that the model is not only innovative in theory but also effective in practical applications.

Figure 6 illustrates the relationship between the increase in the number of beneficial node links and the probability of disruption risk, the proportion of efficiency improvement, and the proportion of resilience enhancement. These data help analyze how optimizing the relationships among nodes in the network can improve the overall performance of the supply chain.

From the data in the figure, it can be observed that the probability of disruption risk decreases as the number of beneficial node links increases, from 0.75 to 0.4. This indicates that increasing beneficial node links can significantly reduce the risk of supply chain disruptions, as the network becomes more interconnected,

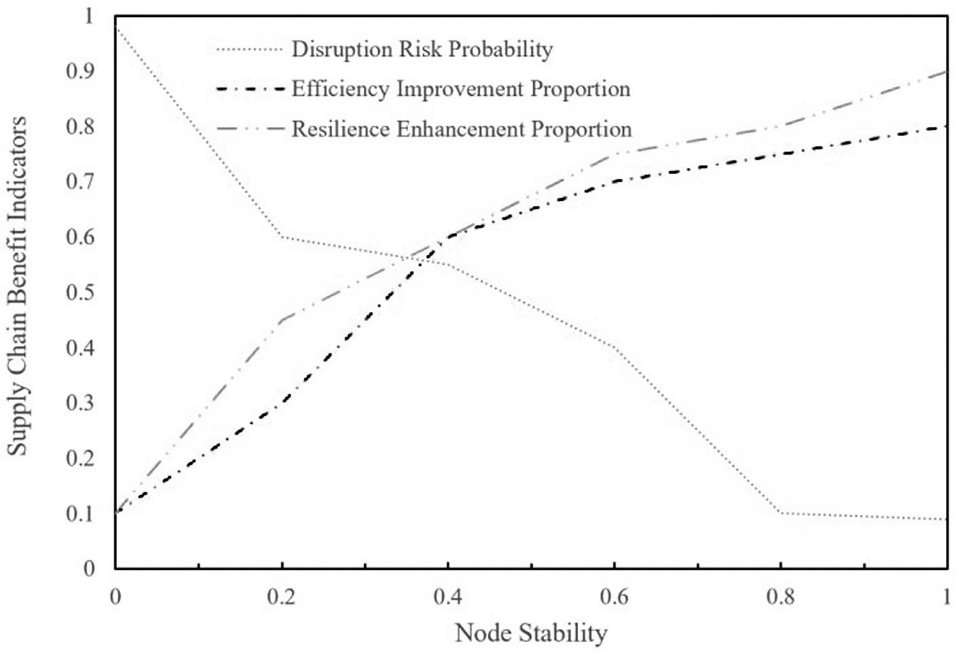

Figure 5. Impact of node stability on supply chain benefit indicators.

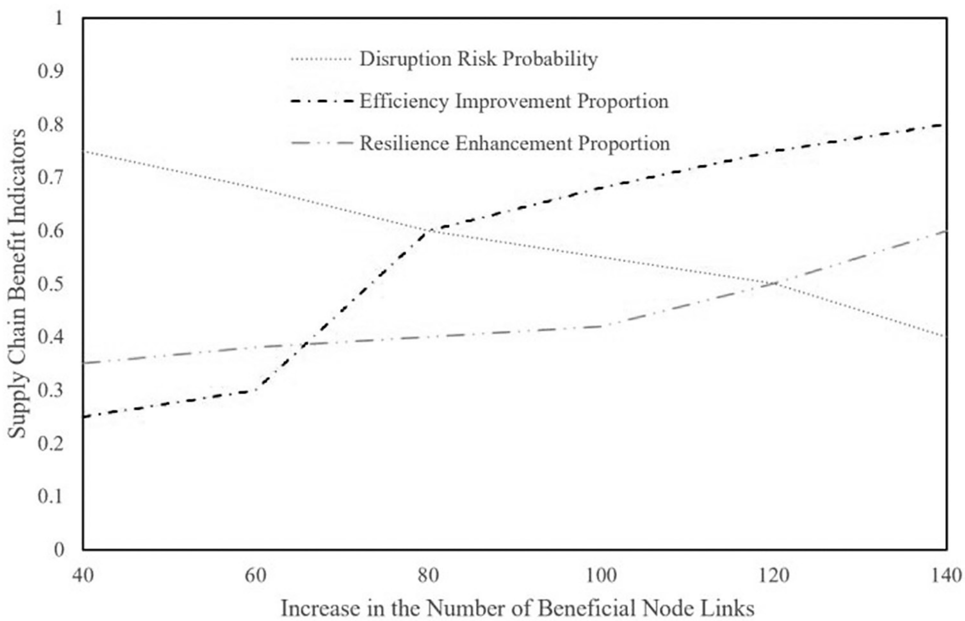

Figure 6. The impact of increased beneficial node link quantity on supply chain benefit indicators.

and the failure of a single node has less impact on the entire network. The proportion of efficiency improvement increases with the number of links, from 0.25 to 0.8. This is due to optimized relationships between nodes and their respective roles, which improves the flow efficiency of information and logistics, reduces redundant steps, and accelerates response times. The proportion of resilience enhancement also increases with the number of links, from 0.35 to 0.6. The resilience of the supply chain refers to its ability to maintain operations or recover quickly in the face of disturbances and stress. Increasing beneficial links enhances the network's redundancy, making it less sensitive to node failures.

It can be concluded that the model constructed in this paper effectively enhances the efficiency and resilience of the supply chain network by increasing beneficial node links, while significantly reducing the risk of disruptions. The intelligence of the model lies in its ability to identify and strengthen links between key nodes in the supply chain, optimizing the structure of the entire network.

Figure 7 shows the relationship between the number of interventions on risk links in the supply chain and the probability of disruption risk, the proportion of efficiency improvement, and the proportion of resilience enhancement. These data reflect the impact of intervention measures on supply chain benefit indicators. The figure indicates that the probability of disruption risk significantly decreases with an increase in the number of risk link interventions, from 0.65 to 0.33. This suggests that targeted interventions have enhanced the robustness of the supply chain network when facing potential disruptions. The proportion of efficiency improvement also gradually increases with the number of interventions, from 0.2 to 0.49. This means that intervention measures not only reduce the risk of disruptions but also improve the overall operational efficiency of the supply chain. Similarly, an increase in the number of interventions leads to an enhancement in the proportion of resilience, from 0.36 to 0.67. This indicates that intervention strategies have strengthened the supply chain's recovery ability and adaptability when facing shocks.

From the GNN model designed in this paper, it is observed that the model successfully enhances efficiency and robustness by intelligently identifying and optimizing the relationships among nodes in the supply chain network. Such optimization not only reduces potential disruption risks in the supply chain but also improves the network's efficiency and resilience. Moreover, by incorporating hierarchical factor analysis, this research allows for a comprehensive assessment of multi-level benefits, providing a more thorough and detailed perspective for quantifying supply chain benefits. This method can capture subtle changes brought about by the optimized supply chain structure through the GNN model and accurately assess its impact on overall benefits.

Combining the above analysis, it can be concluded that this research effectively enhances the efficiency and resilience of the supply chain while significantly reducing disruption risks through the implementation of risk link intervention measures. The effectiveness of the research is clearly demonstrated through data,

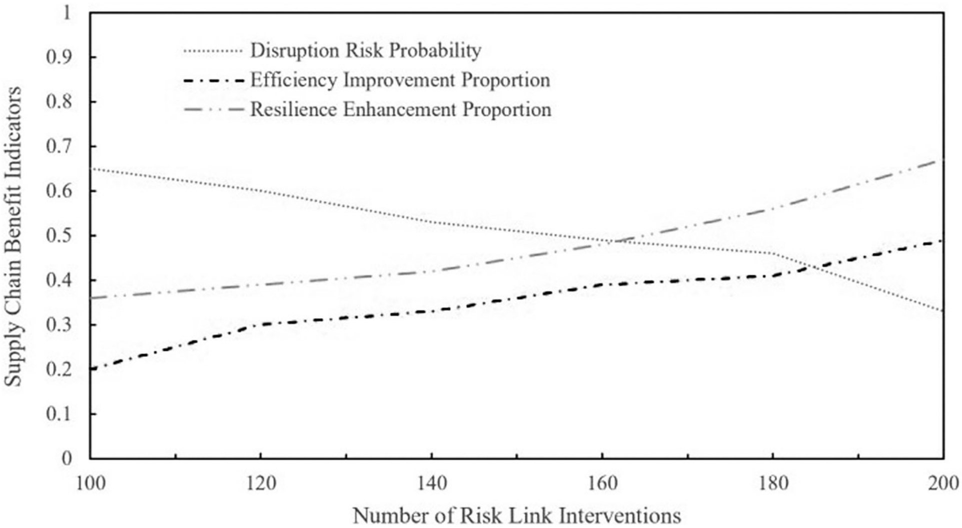

Figure 7. The impact of intervention quantity on risk links on supply chain benefit indicators.

indicating that the GNN model and hierarchical factor analysis have practical application value in supply chain management, offering important decision-support tools for businesses. This not only emphasizes the contribution of the research but also provides strong methodological support for future supply chain risk management and optimization.

The detailed analysis of experimental results underscores the effectiveness and practicality of the method proposed in this paper. First, by conducting experimental analyses on different node relationship optimization measures, researchers were able to better understand the impact of these measures on supply chain performance indicators. Particularly, in areas such as node stability, the increase of beneficial node links, and interventions in risk linkages, the experimental results clearly demonstrated the positive effects of these optimization measures on supply chain performance. Secondly, experimental studies on different node role type injection methods revealed the importance of accurately identifying and utilizing node roles to enhance the performance of the supply chain network. These results further emphasize the critical role of role awareness within the model. Additionally, tests of the model on different datasets confirmed its generalizability and robustness. Whether in the construction of the model or during the node relationship optimization phase, the model successfully adapted to different datasets and effectively generated and optimized node relationship links. This demonstrates the reliability and applicability of the model, enabling its effective use in various real-world scenarios.

5. Conclusion

This study presents an innovative GNN model based on node role type awareness. This model intelligently identifies various nodes and their roles within the production supply chain network, thereby optimizing the relationships among these nodes. The aim of optimization is to enhance the efficiency and robustness of the entire network structure, ensuring the stable operation of the supply chain even in the face of uncertainties and potential risks. The research incorporates hierarchical factor analysis to assess the multi-level benefits of the production supply chain. This method quantifies supply chain benefits comprehensively and in detail, allowing for an understanding of performance improvements and potential risk reductions at different levels.

The paper provides a detailed experimental analysis of the impact of different node relationship optimization measures on supply chain benefit indicators. These benefit indicators include node stability, the increase in beneficial node links, and risk link intervention. The experiments explored the impact of different node role type injection methods on model performance. The results indicate that correctly identifying and utilizing node roles can significantly improve the performance of the supply chain network, including its efficiency and stability. The model's performance was tested across different datasets, showing its success in generating and optimizing node relationship links, thereby enhancing the overall performance of the supply chain. The experiments analyzed the impact of specific node relationship optimization measures on supply chain benefit indicators, finding that improvements in node stability, increases in beneficial node links, and interventions in risk links can effectively enhance the efficiency and resilience of the supply chain and reduce disruption risks.

Although the proposed model has achieved significant results in optimizing the structure of production supply chains and assessing their benefits, it also has some limitations. The method requires a large amount of high-quality data. If the data from the supply chain network is incomplete or of low quality, it may affect the effectiveness and accuracy of the model. The model is relatively complex and requires substantial computational resources to support. For some enterprises with limited resources or lower technical levels, it may be difficult to implement and apply this model. Despite these limitations, our model still has broad applicability in the optimization and performance evaluation of production supply chain networks. Particularly for large manufacturing companies or complex supply chain networks, our method can provide effective decision support, helping to optimize supply chain structures and improve efficiency. Additionally, our model also provides a valuable reference and foundation for future research.

References

[1] J. F. Andry *et al.*, "Critical Factors of Supply Chain Based on Structural Equation Modelling for Industry 4.0", *Journal of European Systems Automation*, vol. 56, no. 2, pp. 187–194, 2023. https://doi.org/10.18280/jesa.560202

[2] E. Kusrini and S. Miranda, "Determining Performance Metrics of Supply Chain Management in Make-to-order Small-medium Enterprise Using Supply Chain Operation Reference model (SCOR Version 12.0)", *Mathematical Modelling of Engineering Problems*, vol. 8, no. 5, pp. 750–756, 2021. https://doi.org/10.18280/mmep.080509

[3] M. Riaz and H. M. A. Farid, "Enhancing Green Supply Chain Efficiency Through Linear Diophantine Fuzzy Soft-Max Aggregation Operators", *Journal of Industrial Intelligence*, vol. 1, no. 1, pp. 8–29, 2023. https://doi.org/10.56578/jii010102

[4] M. Krstić *et al.*, "Strategic Application of Industry 4.0 Technologies in Enhancing Intermodal Transport Terminal Efficiency", *Journal of Organizational Technology and Entrepreneurship*, vol. 1, no. 2, pp. 98–109, 2023. https://doi.org/10.56578/jote010203

[5] G. W. Xu *et al.*, "The Influence of Digital Transformation in Enterprises on the Dynamics of Supply Chain Concentration: An Empirical Analysis of Chinese A-Share Listed Companies", *Journal of Organizational Technology and Entrepreneurship*, vol. 1, no. 2, pp. 88–97, 2023. https://doi.org/10.56578/jote010202

[6] D. Wu *et al.*, "Industry Classification Based on Supply Chain Network Information Using Graph Neural Networks", *Applied Soft Computing*, vol. 132, p. 109849, 2023. https://doi.org/10.1016/j.asoc.2022.109849

[7] J. Li *et al.*, "Tracking Down Financial Statement Fraud by Analyzing the Supplier-customer Relationship Network", *Computers & Industrial Engineering*, vol. 178, p. 109118, 2023. https://doi.org/10.1016/j.cie.2023.109118

[8] L. Alrahis *et al.*, "OMLA: An Oracle-less Machine Learning-based Attack on Logic Locking", *IEEE Transactions on Circuits and Systems II: Express Briefs*, vol. 69, no. 3, pp. 1602–1606, 2021. https://doi.org/10.1109/TCSII.2021.3113035

[9] Y. Wan and X. Bai, "Research on Resource Allocation Management of Industrial Supply Chain Based on Blockchain", *International Journal of Manufacturing Technology and Management*, vol. 37, no. 3–4, pp. 302–314, 2023. https://doi.org/10.1504/IJMTM.2023.133472

[10] M. Drakaki and P. Tzionas, "A Colored Petri Net-based Modeling Method for Supply Chain Inventory Management", *Simulation*, vol. 98, no. 3, pp. 257–271, 2022. https://doi.org/10.1177/00375497211038755

[11] W. Q. Zhuang and Z. Y. Liu, "Build Structure of Fractal Interorganizational Information Systems and Optimize Supply Chain Structure", *Advanced Materials Research*, vol. 468, pp. 268–276, 2012. https://doi.org/10.4028/www.scientific.net/AMR.468-471.268

[12] M. A. Alomar, "Performance Optimization of Industrial Supply Chain Using Artificial Intelligence", *Computational Intelligence and Neuroscience*, 2022, 9306265. https://doi.org/10.1155/2022/9306265

[13] P. Liu *et al.*, "Investment Decision and Coordination of Green Agri-food Supply Chain Considering Information Service Based on Blockchain and Big Data", *Journal of Cleaner Production*, vol. 277, 123646, 2020. https://doi.org/10.1016/j.jclepro.2020.123646

[14] X. Ji and C. Su, "Exploration of Supply Chain Financing Model and Virtual Economic Risk Control Using the Backpropagation Neural Network", *Journal of Global Information Management*, vol. 31, no. 9, pp. 1–20, 2023. https://doi.org/10.4018/JGIM.333605

[15] H. Wang, "Green Supply Chain Optimization Based on BP Neural Network", *Frontiers in Neurorobotics*, vol. 16, 865693, 2022. https://doi.org/10.3389/fnbot.2022.865693

[16] C. Lima *et al.*, "A Graph Modeling Framework to Design and Plan the Downstream Oil Supply Chain", *International Transactions in Operational Research*, vol. 29, no. 3, pp. 1502–1519, 2022. https://doi.org/10.1111/itor.12969

[17] L. Moretti *et al.*, "A Detailed MILP Formulation for the Optimal Design of Advanced Biofuel Supply Chains", *Renewable Energy*, vol. 171, pp. 159–175, 2021. https://doi.org/10.1016/j.renene.2021.02.043

[18] T. Jiang *et al.*, "Market Equilibrium in Multi-tier Supply Chain Networks", *Naval Research Logistics (NRL)*, vol. 69, no. 3, pp. 355–370, 2022. https://doi.org/10.1002/nav.22022

[19] R. Sujitha *et al.*, "A Study on Impact of Industry 4.0 on Supply Chain Efficiency Among Manufacturing Firms", in *Industry 4.0 and Advanced Manufacturing: Proceedings of I-4AM 2022*, 2022, pp. 385–396. https://doi.org/10.1007/978-981-19-0561-2_34

[20] Y. Madhwal *et al.*, "Enhancing Supply Chain Efficiency and Security: A Proof of Concept for IoT Device Integration with Blockchain", *IEEE Access*, vol. 11, pp. 121173–121189, 2023. https://doi.org/10.1109/ACCESS.2023.3328569

[21] G. Li, "Supply Chain Efficiency and Effectiveness Management Using Decision Support Systems", *International Journal of Information Systems and Supply Chain Management (IJISSCM)*, vol. 15, no. 4, pp. 1–18, 2022. https://doi.org/10.4018/IJISSCM.305847

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