Research on the Application of Knowledge Graph Technology in Supply Chain Network Relationship Mining and Collaborative Management

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ABSTRACT The conventional relational mining techniques, which rely on statistical analysis or single-graph modeling approaches, exhibit several major limitations, including weak capability for multi-source heterogeneous data fusion, insufficient performance in identifying implicit relationships, and limited support for collaborative decision-making.To address these issues, this paper proposes a novel methodological framework that leverages knowledge graphs for relational mining and collaborative management in supply chain networks. Specifically, by integrating rule-based mining with deep learning methods, the framework enables a unified structured representation of multi-source data (orders, logistics, and enterprise relationships) and constructs a dynamic supply chain knowledge graph. Furthermore, graph computation and graph embedding techniques are employed to capture the topological structure of the supply chain network, while centrality analysis and link prediction are used to identify key nodes and infer latent relationships.Experimental results demonstrate that the proposed method achieves significant improvements in both relational mining and collaborative decision-making tasks. In particular, the network density increases to 0.093 while preserving the sparse characteristics of real-world supply chain networks; the average path length decreases to 3.05; the link prediction AUC reaches 0.91; and the accuracy of key node identification improves to 0.81. Regarding collaborative optimization performance, the proposed approach achieves a cost reduction of 23.5%, a time reduction of 19.6%, and a risk control improvement of 41 %.

INDEX TERMS supply chain network,knowledge graph,relationship mining,collaborative optimization,risk propagation

I. INTRODUCTION

UNDER the intensifying trends of globalization and the digital economy, supply chain networks are becoming increasingly complex, characterized by structural heterogeneity, diversified interactions, and highly dynamic evolution. Beyond explicit transactional and logistical relationships among enterprises, supply chain systems also involve implicit dependencies and risk propagation pathways, which collectively drive the system toward a highly coupled and complex network structure.

To address these challenges, this study proposes a methodological framework for supply chain relationship mining and collaborative management based on knowledge graph technology. The framework integrates rulebased extraction and deep learning methods to enable structured representation and dynamic construction of supply chain knowledge graphs. Furthermore, graph computing and graph embedding techniques are employed to model and analyze the network topology, where key nodes identification and link prediction are used to uncover latent relationships within the network.

On this basis, rule reasoning and representation learning are jointly applied to support knowledge graph completion and relationship inference, thereby enabling a multi-objective collaborative optimization frame work for supply chain decision-making.

II. RELATED WORK

With the growing application of data-driven and intelligent technologies in supply chain management, research has shifted from single-objective optimization to multi-factor coupling and complex network perspectives, focusing on supply chain operational mechanisms and decision optimization. As data elements, network structures, and intelligent algorithms become increasingly integrated, improving forecasting accuracy and collaborative efficiency through multi-source data mining has become a key research direction. Previous studies have addressed related issues from different perspectives. Xu et al. developed the FA-SSA-BP cost prediction model by integrating data mining techniques with multi-factor analysis, achieving high predic tion accuracy in power equipment manufacturing cost control [1]. Li and Liu examined how data elements influence supply chain resilience and found that data enhances resilience through information innovation and transmission, though effects vary across organizations and contexts [2]. Wang et al. empirically showed that firms' centrality and structural hole positions in supply chain networks positively affect total factor productivity under digital transformation [3]. Liu and Chen analyzed a product-service supply chain using a two-stage game model and found that data sharing improves both firm profit and decision-making in pricing and service strategies [4].

In terms of data preprocessing and modeling, Niu proposed a method combining LOF and change point detection for data cleaning in power equipment manufacturing, and applied SSAE-LASSO for noise reduction and dimensionality compression [5]. Yang et al. built a TERGM model to capture dynamic interactions between collaboration and litigation networks, revealing transition mechanisms under reciprocity and retali ation strategies [6]. Wang et al. proposed the MF-IAMGCN model to model temporal information diffusion using multi-layer networks and mixed-frequency data, improving prediction performance in asset pricing and portfolio optimization [7].

In summary, although significant progress has been made in data mining, network analysis, and predictive modeling, three key limitations remain. First, most studies focus on isolated tasks such as prediction or game-theoretic analysis, lacking an integrated framework that connects relationship mining, structural analysis, and collaborative decision-making. Second, unified semantic representation and dynamic modeling of heterogeneous multi-source data remain insufficiently explored, limiting a comprehensive understanding of supply chain relationships. Third, implicit relationship discovery and cross-entity collaboration mechanisms require further attention. Therefore, future research should integrate knowledge graph and graph computing methods to enable unified multi-source data fusion, relationship reasoning, and collaborative optimization.

III. METHODS

A. OVERALL FRAMEWORK OF SUPPLY CHAIN RELATIONSHIP MINING AND COLLABORATIVE OPTIMIZATION

Multi-source data extraction and structured representation methods

To address the challenges of heterogeneous data integration, dynamic relationship evolution, and collabora tive decision-making in supply chain networks, this study proposes a knowledge graph-driven framework for supply chain relationship mining and collaborative optimization.

The proposed framework consists of four stages:

(1) multi-source data extraction and structured representation;

(2) entity recognition and relation extraction;

(3) dynamic knowledge graph construction and evolution; and

(4) graph-based relationship mining and collaborative optimization.

First, heterogeneous supply chain data are transformed into unified graph representations through structured semantic mapping. Second, entity recognition and relation extraction models are employed to identify supply chain entities and semantic associations from textual data. Third, a dynamic knowledge graph updating mechanism is introduced to capture temporal evolution and continuously maintain the supply chain network structure. Finally, graph computing, representation learning, and reasoning methods are integrated to support latent relationship discovery and collaborative optimization.

The overall framework provides unified support for multi-source data fusion, network topology analysis, and intelligent decision-making in complex supply chain systems.

In the structured representation process, supply chain elements are abstracted into triples to achieve a graph-based representation $G = (E, R, T)$. Here, E represents the set of entities (enterprises, products, nodes, etc.), R represents the set of relationships (transactions, transportation, dependencies, etc.), and T represents the set of triples. Any knowledge unit can be represented as:

$$t = (h, r, t), h, t \in E, r \in R \tag{1}$$

To unify the semantic representation of different data sources, a mapping function (f) is introduced to convert the original data (x) into graph triples:

$$f(x) \to (h, r, t) \tag{2}$$

The above methods enable the mapping of multi-source heterogeneous data to a unified knowledge repre sentation space, providing a foundation for subsequent relationship mining.

B. ENTITY RECOGNITION AND RELATION EXTRACTION MODEL DESIGN

The text sequence is labeled using a named entity recognition model. The input sequence is represented as $X = x_1, x_2, \ldots, x_n$. The corresponding label sequence is $Y = y_1, y_2, \ldots, y_n$. The optimal labeling result is achieved by maximizing conditional probability.

$$Y^* = \arg\max_Y P(Y|X) \tag{3}$$

In the relation extraction stage, a relation classification model based on context representation is introduced to determine the semantic relationships between entity pairs.

For any entity pair (e_i, e_j), its relation prediction can be expressed as:

$$r_{ij} = \arg\max_{r \in R} P(r|e_i, e_j, X) \tag{4}$$

Furthermore, through a joint learning mechanism, entity recognition and relation extraction are optimized end-to-end, and the overall objective function can be expressed as $\mathcal{L} = \mathcal{L}_{NER} + \lambda \mathcal{L}_{RE}$, where λ is the weight coefficient used to balance the contributions between the two tasks.

C. DYNAMIC UPDATE AND EVOLUTION MECHANISM OF KNOWLEDGE GRAPH

The knowledge unit is extended based on the timestamp mechanism, and the traditional triple is represented as a quadruple with a time dimension $t = (h, r, t, \tau)$. Here, τ represents time information and is used to describe the time node when the relationship occurs or changes.

During the knowledge graph update process, an incremental update strategy is introduced, which only updates newly added or changed data locally:

$$G_t = G_{t-1} \oplus \Delta G.$$

Its update function can be expressed as: where G_t represents the knowledge graph at the current time, and ΔG represents the newly added or changed knowledge subgraph.

To further characterize the evolution of relationships, a time decay function is introduced to assign different weights to historical relationships:

$$w(t) = e^{-\beta(t-\tau)} \tag{5}$$

Here, β is the decay coefficient, $(t - \tau)$ representing the interval between the current time and the time when the relationship occurred. This mechanism can highlight the importance of recent relationships while retaining historical information for trend analysis.

D. METHODS FOR SUPPLY CHAIN NETWORK RELATIONSHIP MINING AND STRUCTURAL FEATURE ANALYSIS

1) Supply Chain Network Topology Modeling Based on Graph Computation

Based on the constructed supply chain knowledge graph, this section further investigates network relation ship mining and structural feature analysis through graph computation and graph embedding techniques. The objective is to identify critical enterprise nodes, quantify relationship strength, and discover potential collaborative relationships within complex supply chain networks.

The proposed analysis framework consists of three stages:

(1) supply chain network topology modeling through graph computation;

(2) key node identification and relationship strength assessment; and

(3) latent relationship mining and link prediction based on graph embedding methods.

First, a multi-layer attributed graph is constructed to represent heterogeneous supply chain interactions. Second, graph centrality indicators and weighted relationship measures are employed to evaluate the struc tural importance and collaborative intensity of enterprise nodes. Finally, graph embedding and supervised link prediction methods are integrated to uncover hidden relationships and support collaborative optimization tasks.

The supply chain knowledge graph is modeled as an attributed directed graph, in which enterprises, products, logistics nodes, and other entities are represented as graph nodes, while transaction, transportation, and collaboration relationships are represented as directed edges. The complex interactions among enterprises are further characterized through multi-dimensional node and edge attributes. Based on this representation, an adjacency matrix is introduced to formally describe the network topology:

$$A = [a_{ij}]_{n \times n} \tag{6}$$

where

$$a_{ij} = \begin{cases} w_{ij}, & (v_i, v_j) \in E, \\ 0, & \text{otherwise} \end{cases} \tag{7}$$

Here, A_{ij} represents the connection relationship between node v_i and node v_j, while w_{ij} denotes the edge weight, which may reflect transaction frequency, logistics intensity, cooperation stability, or other relational attributes.

To further characterize heterogeneous supply chain interactions, a multi-layer network model is constructed by separating different relationship types into multiple subnetworks, including capital flow networks, logistics flow networks, and information flow networks. The overall supply chain network can therefore be expressed as:

$$G = G^{(1)}, G^{(2)}, \cdots, G^{(m)} \tag{8}$$

where $G^{(k)} = (V^{(k)}, E^{(k)})$ represents the subgraph corresponding to the k-th relationship type, and m denotes the total number of network layers.

To integrate heterogeneous relationships across different layers, a weighted graph fusion strategy is intro duced. The unified supply chain network is represented as:

$$G^* = \sum_{k=1}^{m} \omega_k G^{(k)} \tag{9}$$

where ω_k denotes the fusion weight of the k-th network layer and satisfies:

$$\sum_{k=1}^{m} \omega_k = 1 \tag{10}$$

In this study, the layer weights are assigned according to the relative importance of different relationship types in collaborative supply chain operations. Among them, logistics flow relationships are assigned relatively higher weights because they directly affect operational connectivity and resource scheduling efficiency, followed by capital flow and information-sharing relationships. Moreover, all edge weights are normalized before fusion to ensure comparability among heterogeneous network layers.

Through the weighted multi-layer fusion mechanism, the proposed model can preserve both the structural heterogeneity and the cross-layer interaction characteristics of the supply chain network, thereby enabling a unified knowledge representation space for subsequent relationship mining, link prediction, and collaborative optimization tasks.

2) Key Node Identification and Relationship Strength Assessment Method

In supply chain networks, different nodes play significantly different roles within the structure. Therefore, graph computation methods are needed to identify key enterprise nodes and quantify their importance within the network. First, degree centrality is used to measure the direct connectivity of nodes $C_D(v_i) = \sum_j A_{ij}$. Second, betweenness centrality is introduced to characterize the mediating role of nodes in network paths.

$$C_B(v) = \sum_{s \neq v \neq t} \frac{\sigma_{st}(v)}{\sigma_{st}} \tag{11}$$

Here, σ_{st} represents the number of shortest paths from node s to node t, and $\sigma_{st}(v)$ represents the number of paths passing through node v. This metric can be used to identify key nodes that act as "bridges" in the supply chain.

In assessing relationship strength, a weighted relationship strength function is introduced, taking into account transaction frequency, transaction size, and cooperation stability:

$$S_{ij} = \alpha f_{ij} + \beta m_{ij} + \gamma d_{ij} \tag{12}$$

Here, f_{ij} represents transaction frequency, m_{ij} represents transaction amount, d_{ij} represents cooper ation duration, and α, β, and γ are weighting parameters. This indicator can quantify the closeness and dependence of relationships between enterprises.

3) Potential Relationship Mining and Link Prediction Methods

Node representations are learned through graph embedding methods $z_i = f(v_i)$. Here, z_i is the low-dimen sional vector representation of a node v_i, and the function f achieves embedding learning by preserving graph structural similarity. During link prediction, potential connections are predicted by measuring the similarity between node vectors; common methods include inner product or distance functions.

$$P_{ij} = \sigma(\mathbf{z}_i^T \mathbf{z}_j) \tag{13}$$

Here, $\sigma(\cdot)$ is the Sigmoid function, used to map the prediction result to a probability value.

Furthermore, to improve prediction accuracy, a link prediction model based on supervised learning can be constructed, whose optimization objective function can be expressed as follows

$$\mathcal{L} = -\sum_{(i,j)\in E} \log P_{ij} - \sum_{(i,j)\notin E} \log(1 - P_{ij}).$$

By minimizing this loss function, we can learn to distinguish between existing and potential relationships.

E. COLLABORATIVE REASONING AND OPTIMIZATION METHODS

1) Graph Reasoning Mechanism Based on Rule and Representation Learning

Based on the supply chain network structure and latent relationship mining results obtained in Section 3.2, this section further investigates collaborative reasoning, optimization, and risk control mechanisms within the supply chain network. The objective is to enhance relationship inference capability, optimize collaborative decision-making paths, and improve network resilience under dynamic risk propagation conditions.

The proposed framework consists of three components:

(1) graph reasoning based on rule learning and representation learning;

(2) multi-objective collaborative optimization path modeling; and

(3) graph-based risk propagation analysis and collaborative control.

First, rule reasoning and knowledge representation learning are jointly employed to improve knowledge graph completeness and infer hidden relationships. Second, a multi-objective optimization model is constructed to balance cost, efficiency, and risk in collaborative supply chain operations. Finally, a graph-based risk propagation model is introduced to analyze risk diffusion processes and support dynamic collaborative control strategies.

At the rule-based reasoning layer, first-order logic rules are introduced to deductively infer relationships. For example, rules can be defined for transmission relationships in a supply chain $(h, r_1, m) \wedge (m, r_2, t) \Rightarrow (h, r_3, t)$.

To quantify the confidence level of a rule's validity, a rule scoring function is introduced:

$$\text{Score}_{rule} = \frac{|(h,m,t) \in G : (h, r_1, m) \wedge (m, r_2, t)|}{|(h,m,t) \in G : (h, r_1, m) \wedge (m, r_2, t)| + \epsilon} \tag{14}$$

In the representation learning layer, entities and relations are vectorized using a knowledge graph embedding model, transforming relational reasoning into a computational problem in a vector space. A typical represen tation is as follows:

$$\mathbf{h} + \mathbf{r} \approx \mathbf{t} \tag{15}$$

Here, $\mathbf{h}$, $\mathbf{r}$, and $\mathbf{t}$ represent the vector representations of the head entity, relation, and tail entity, respectively. Combining the two methods, a joint inference objective function is constructed:

$$\mathcal{L} = \mathcal{L}_{embed} + \lambda\mathcal{L}_{rule} \tag{16}$$

Wherein, (λ) represents the weighting parameter. This mechanism can improve reasoning coverage while ensuring logical consistency, thereby enhancing the expressive completeness of the supply chain knowledge graph.

2) Collaborative Optimization Path Modeling Method

The paths in the supply chain network are represented as a sequence of nodes $P = v_1, v_2, \ldots, v_n$. Based on this, a multi-objective optimization function is defined, comprehensively considering cost, efficiency, and risk factors:

$$\min F(P) = \alpha C(P) + \beta T(P) + \gamma R(P).$$

where $C(P)$, $T(P)$, and $R(P)$ denote path cost, transportation or response time, and path risk, respectively, while α, β, and γ are weighting coefficients satisfying:

$$\alpha + \beta + \gamma = 1 \tag{17}$$

Where $C(P)$ represents the path cost, $T(P)$ represents the transportation or response time, $R(P)$ represents the path risk, and α, β, and γ are weighting coefficients.

Each sub-objective function can be further expressed as:

$$\begin{aligned} C(P) &= \sum_{(i,j)\in P} c_{ij}, \\ T(P) &= \sum_{(i,j)\in P} t_{ij}, \\ R(P) &= \sum_{(i,j)\in P} r_{ij} \end{aligned} \tag{18}$$

By introducing constraints (such as capacity constraints and time constraints), a complete optimization model is constructed:

$$\text{s.t.} \quad g_k(P) \le 0, \quad k = 1, 2, \ldots, K \tag{19}$$

This method can find the optimal collaborative path under multiple objective trade-offs, thereby achieving overall optimization of supply chain resource allocation.

3) Risk Propagation Analysis and Collaborative Control Mechanism

Supply chain networks are highly interconnected, and localized risk events can spread rapidly through these networks. Therefore, it is necessary to construct a graph-based risk analysis model to characterize the risk diffusion path and the scope of its impact.

First, the risk state of a node is represented as a time function $x_i(t) \in [0, 1]$, where it represents the risk level of node i at time t. Based on the graph structure, the risk propagation process can be modeled as follows:

$$x_i(t+1) = \sum_{j\in N(i)} w_{ji} x_j(t) \tag{20}$$

Where $N(i)$ represents the set of neighbors of node i, and w_{ji} represents the risk propagation weight. To prevent the risk from spreading indefinitely, attenuation and regulation mechanisms are introduced to construct an improved propagation model:

$$x_i(t+1) = (1-\delta)x_i(t) + \eta \sum_{j\in N(i)} w_{ji} x_j(t) \tag{21}$$

Where δ is the risk attenuation coefficient, and η is the propagation intensity parameter.

Based on this, a risk warning model is constructed by combining a threshold mechanism:

$$\text{Alert}_i = \begin{cases} 1, & x_i(t) \ge \theta, \\ 0, & x_i(t) < \theta \end{cases} \tag{22}$$

Here, θ represents the early warning threshold. When the risk of a node exceeds the threshold, an early warning is triggered, and coordinated control is achieved by adjusting the weight of key edges or path strategies.

Through the integration of graph reasoning, collaborative optimization, and risk propagation control, the pro posed framework enables unified support for supply chain relationship inference, intelligent decision-making,

and dynamic risk management. The overall methodology further enhances the adaptability, resilience, and collaborative efficiency of complex supply chain networks,as shown in Figure 1.

IV. METHOD VALIDATION AND RESULT ANALYSIS DESIGN

A. EXPERIMENTAL DATA CONSTRUCTION AND PROCESSING METHODS

We collect multilateral data regarding the process of supply chain management, which comprises enterprise business transaction data, logistics route data, and public data on enterprise relationships to create our initial dataset consisting of entities and relations. Then, through data cleansing and normalization, we make our data standardized in field types and semantics to generate basic data that can be used to construct our knowledge graph.

The triplet data extracted is categorized into training set and test set data, and entities and relations are encoded. Then, using negative sampling, we generate our contrast samples to train models for link prediction and relation prediction tasks. Our approach to negative sampling can be expressed by $(h, r, t') \notin G$ or $(h', r, t) \notin G$.

The experimental dataset was constructed using multi-source supply chain data collected from manufacturing and logistics enterprises located in Eastern China from January

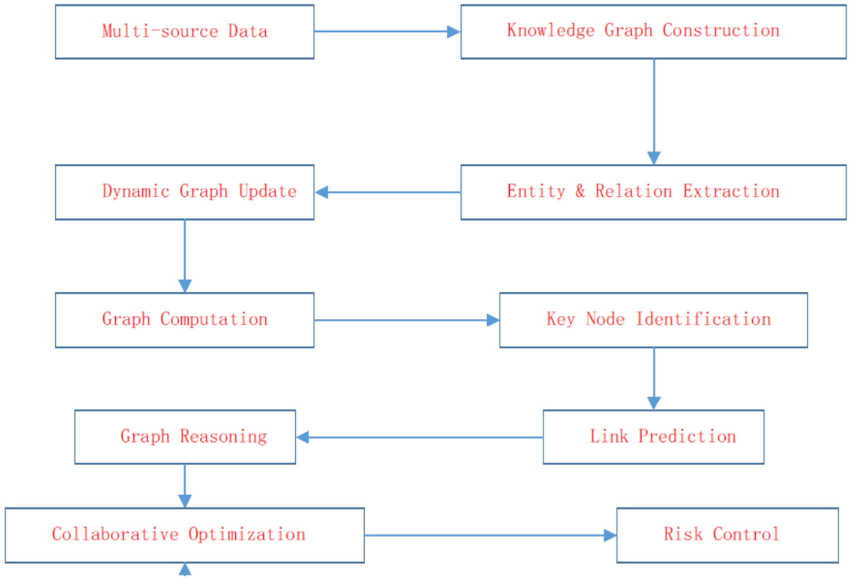

FIGURE 1. Knowledge Graph-Driven Framework for Supply Chain Relationship Mining and Collaborative Optimization

2021 to December 2023. The dataset contains approximately 12,500 entities and 48,000 relationship triples, covering enterprise transactions, logistics transportation routes, supplier cooperation relationships, and information-sharing interactions. After data cleaning and semantic normalization, the heterogeneous data were transformed into a unified knowledge graph representation for subsequent relationship mining and collaborative optimization tasks.

B. VALIDATION DESIGN OF SUPPLY CHAIN RELATIONSHIP MINING METHOD

For the graph structure model constructed in 3.2.1, its structural rationality is evaluated based on indicators such as network density, average path length, and clustering coefficient. The network density is calculated as follows:

$$D = \frac{2|E|}{|V|(|V|-1)}$$

and is used to measure the tightness of the supply chain network connections. Key nodes are ranked based on centrality indicators, and the effectiveness of the method is evaluated by comparing them with core enterprises in the actual supply chain (such as nodes with high transaction frequency). A ranking consistency index is used for quantification:

$$\rho = 1 - \frac{6\sum d_i^2}{n(n^2-1)}.$$

Here, d_i represents the ranking difference, used to measure the degree of consistency between the identified results and the true distribution.

For the task of latent relationship mining, a link prediction evaluation metric is introduced, including accuracy TP and AUC. Prediction accuracy is defined as follows:

$$\text{Precision} = \frac{TP}{TP+FP}.$$

Simultaneously, the overall discriminative ability of the model is evaluated using ROC curves, thereby validating the effectiveness of the graph embedding and link prediction methods.

C. VALIDATION DESIGN OF COLLABORATIVE MANAGEMENT AND DECISION SUPPORT METHODS

For the inference mechanism in section 3.3.1, the link prediction hit rate (Hits@K) and average ranking

(MRR) are used for evaluation. MRR is defined as

$$\text{MRR} = \frac{1}{N}\sum_{i=1}^{N}\frac{1}{\text{rank}_i},$$

a measure of the overall ranking performance of the inference results.

The supply chain paths before and after optimization are compared, and a quantitative analysis is conducted across three dimensions: cost, time, and risk. The path optimization improvement rate is defined as

$$\Delta F = \frac{F_{\text{before}} - F_{\text{after}}}{F_{\text{before}}},$$

the degree to which the collaborative optimization method improves overall performance. Based on a risk propagation model, the risk diffusion process is simulated, and the risk change trends at key nodes are statistically analyzed. The risk control rate indicator is used to evaluate the effectiveness of the control measures:

$$R_c = 1 - \frac{\sum_i x_i^{\text{after}}}{\sum_i x_i^{\text{before}}}.$$

As seen in Figure 2, there are significant differences among various methods in supply chain network relationship mining performance. Overall, the proposed method demonstrates superior performance across all evaluation

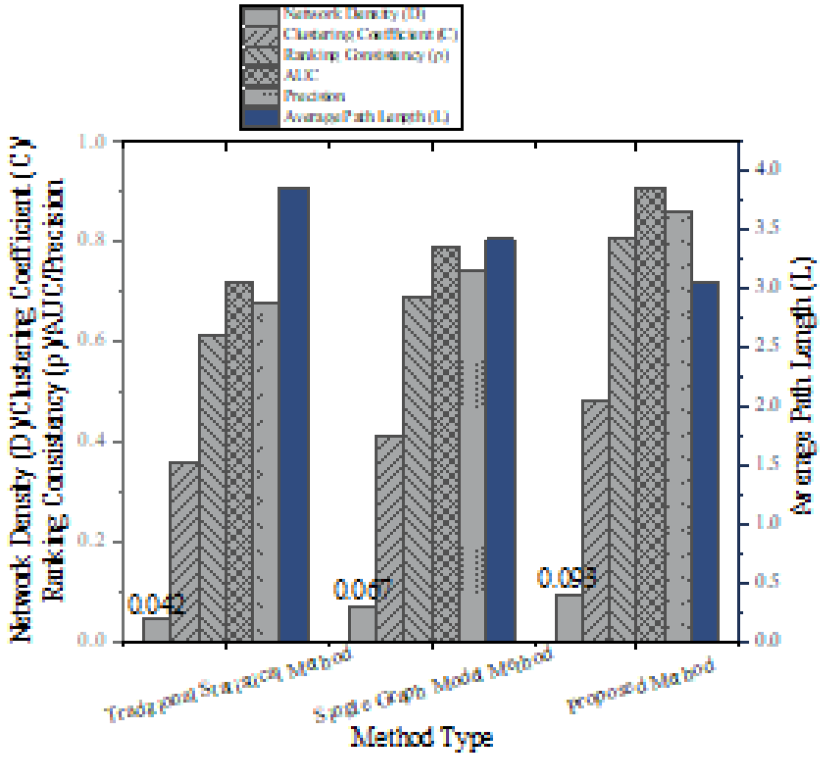

FIGURE 2. Performance evaluation results of the supply chain network relationship mining method

indicators, indicating strong comprehensive effectiveness. Regarding network structural char acteristics, the proposed method achieves a network density of 0.093, which is higher than that of the traditional statistical method (0.042) and the single graph model method (0.067). This result indicates that the proposed multi-source data fusion and graph modeling strategy improves the effective connectivity among enterprise nodes while still maintaining the sparse structural characteristics commonly observed in real-world supply chain networks. Meanwhile, the average path length decreases from 3.87 to 3.05, suggesting that the efficiency of information transmission and collaborative interaction within the supply chain network is effectively enhanced. In terms of relationship mining capability, the ranking consistency improves from 0.61 to 0.81, demonstrating that the proposed method is more consistent with the actual supply chain structure when identifying core enterprise nodes and important network relationships.

TABLE 1. Comparison of the effects of collaborative management and decision support methods

Method type	Hits@10	MRR	Cost reduction rate ΔC	Time reduction rate ΔT	Risk control rate R_c
Rule-based reasoning methods	0.62	0.48	12.30%	10.70%	21%
Embedded learning methods	0.71	0.56	16.80%	14.20%	28%
This article's method	0.83	0.67	23.50%	19.60%	41%

As indicated in Table 1, various approaches show a continuous enhancement in collaboration management and decision support effectiveness. In contrast, the approach proposed in this paper shows outstanding performance and demonstrates the highest comprehensive strengths in all metrics. With respect to graph inference ability, the proposed approach obtains a score of 0.83 in Hits@10 metric, which exceeds 0.21 and 0.12 compared with the traditional rule-based approach (0.62) and embedding learning approach (0.71). Therefore, it can be concluded that the proposed integration model can better boost the possibility of correct relationships being ranked high. At the same time, the value of MRR increases from 0.48 and 0.56 to 0.67, revealing that the proposed technique has superior ranking efficiency, accurate identification of real relation ships, and improved reasoning credibility.

V. CONCLUSION

In this work, This paper solve the problems of relation modeling and collaborative management efficiency improvement in complicated supply chain networks through designing a knowledge graph-oriented approach for relation extraction and collaborative decision-making. Firstly, multi-source heterogeneous data integration and dynamic knowledge graphs modeling can provide a uniform representation for supply chain entities. Then, with the combination of graph computations and graph embeddings, the mining of significant nodes and relations becomes more effective. Finally, a mechanism combining rule-based reasoning and representation learning fusion, and an optimization model for collaboration and risk propagation are established to enable comprehensive control on costs, timeliness, and risks. Experiments show that our approach outperforms comparative algorithms in relation identification, link prediction ability, and collaborative optimization effects, which indicates its effectiveness and practicality in complicated supply chain scenarios. It should be pointed out that there are some drawbacks of this study, such as the neglect of computational efficiency and dynamic updating ability when facing ultra-large scale and real-time data. The future research direction may involve incorporating distributed computing and real-time stream processing into the proposed algorithm for improving applicability and generalization of the model in realistic scenarios.

AUTHOR CONTRIBUTIONS

Xin Guo designed, collected and analyzed the data, and drafted the manuscript. Xin Guo conducted the study, critically revised the manuscript for important intellectual content, and gave final approval of the version to be published. Xin Guo participated fully in the work, take public responsibility for appropriate portions of the content, and agreed to be accountable for all aspects of the work in ensuring that questions related to the accuracy or integrity of any part of the work are appropriately investigated and resolved.

CONFLICTS OF INTEREST

The author declares no conflict of interest.

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