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The Role of Deep Learning in Supply Chain Collaboration and Cooperation

Junjie Cai, Universiti Putra Malaysia, Bintulu, Malaysia*
Ismawati Sharkawi, Universiti Putra Malaysia, Bintulu, Malaysia
Shairil Izwan Taasim, Universiti Putra Malaysia, Bintulu, Malaysia

ABSTRACT

In today's globalized and technologically advanced business landscape, supply chain collaboration is crucial for enterprises seeking to gain a competitive edge, enhance operational efficiency, and adapt to market dynamics. Traditional methods often fall short in managing the complexities and rapid changes within supply chains. This study introduces an innovative deep learning model, combining BERT, GAT, and RL, to address these challenges effectively. The model demonstrates its prowess in processing supply chain data, accurately predicting market trends, and optimizing decision-making processes. By leveraging deep learning, this research not only expands theoretical applications in supply chain management but also provides practical tools to boost operational efficiency, highlighting the immense potential and practical value of deep learning technology in modern supply chain management.

KEYWORDS

BERT, Deep Learning, GAT, RL, Supply Chain

INTRODUCTION

In today's fast-changing global marketplace, supply chain collaboration and cooperation have become key to achieving efficiency and responsiveness (Qin & Guo, 2021). Supply chain collaboration and cooperation refers to the coordination and cooperation between different organizations in a supply chain to achieve a common goal (Hanga & Kovalchuk, 2019). These practices involve the coordination among organizations to optimize supply chain performance, which enhances efficiency, reduces costs, and improves customer satisfaction (Zhang et al., 2023). Driven by globalization and technological advances, supply chain collaboration and cooperation have become particularly important (Wankmüller &Reiner, 2019). However, achieving effective supply chain collaboration and cooperation faces many challenges, such as the security of information sharing, the conflict of goals among different organizations (LI Yueze, 2023), and the difficulty of data processing and analysis in complex supply chain structures.

In recent years, deep learning technology has emerged as a key solution to supply chain collaboration issues (Yuxiang et al., 2021). The ability of deep learning lies in that it could effectively

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extract information from complex data, deepening our understanding of supply chain dynamics, optimizing decision-making processes, and predicting trends (Liu et al., 2022). Deep learning models such as convolutional neural networks (CNNs), recurrent neural networks (RNNs), and graph neural networks (GNNs) have been used in a variety of areas such as demand forecasting (Nunes et al., 2020), inventory management, and supply chain risk assessment, demonstrating strong computational and analytical forecasting capabilities.

Based on the shortcomings of the above work, we introduce the Bidirectional Encoder Representation Transformer (BERT)-graph attention network (GAT)-reinforcement learning (RL) model to address supply chain collaboration challenges. The BERT-GAT-RL model aims to enhance data processing and decision-making in supply chains. In this model, the BERT part is responsible for processing and understanding supply chain textual data, such as communication records of suppliers and customers; the GAT part is used to analyze complex relationships and influences in the supply chain network; and the RL part explores optimal supply chain decision-making strategies in a simulation environment.

The innovation of our paper is the integration of the BERT, GAT, and RL models for a comprehensive approach to challenges in supply chains and the ability to deal with multiple issues in supply chain collaboration and cooperation in a more holistic way. This combination leads to more accurate and efficient supply chain decisions and promotes better collaboration among stakeholders. BERT is used for processing textual data within the supply chain, such as communication records. Its bidirectional nature allows it to capture contextual information effectively, improving the efficiency of using textual data in supply chain management. GAT is employed to analyze complex relationships and influences within the supply chain network. By leveraging attention mechanisms, GAT can focus on relevant nodes in the network, aiding in the structuring of complex supply chain relationships. RL is utilized to explore optimal supply chain decision-making strategies in a simulation environment. RL's ability to learn from interactions with the environment enables it to adapt and optimize decisions in dynamic supply chain scenarios.

The combination of these three models offers a comprehensive approach to addressing supply chain challenges, particularly in data processing and decision-making. Each individual model has been proven effective in various tasks within their respective domains. By integrating these models, we aim to leverage their strengths and offer a more holistic solution to supply chain collaboration and cooperation challenges. Our model not only delivers accurate predictions and insights into supply chain collaboration but also merges the strengths of its components to offer flexibility and accuracy in big data management. With this approach, we can better understand and predict dynamic changes in the supply chain, thus providing stronger support for supply chain management. Our proposed TCN-BILSTM-attention network model has important theoretical and practical significance in the field of supply chain collaboration and cooperation. This approach improves understanding and prediction of supply chain dynamics and induces significant theoretical and practical benefits for supply chain management.

The contribution points of this paper are as follows:

- We provide an effective technological path for the intelligence and automation of supply chain collaboration and cooperation: our research not only showcases the impact of deep learning on supply chain management, but also provides both a theoretical foundation and practical guidelines for future research and practice of related technologies. In particular, our work is of great guiding significance in promoting supply chain information sharing, optimizing the decision-making process, and enhancing the overall supply chain efficiency.
- We provide an effective technological path for the intelligence and automation of supply chain collaboration and cooperation: our research not only demonstrates the potential of deep learning technologies in supply chain management, but also provides a theoretical foundation and

operational guidelines for future research and practice of related technologies. This innovation gives a strong boost to decision-making accuracy and efficiency in supply chain management.

- We pioneer the integration of BERT, GAT, and RL models in supply chain collaboration. Through this innovative fusion approach, we are able to synthesize and analyze textual data, network structures, and decision-making processes in supply chains. This unique combination improves accuracy and efficiency in decision-making and offers novel insights and tools for enhanced collaboration and cooperation in supply chains.

The logical structure of this paper is as follows. Related Work reviews and discusses in detail the relevant research in the field of supply chain collaboration and cooperation. In Methodology, we describe in detail BERT, GAN, and RL used in our approach. Experiments covers the hardware and software environments in which the experiments are conducted. In addition, we define and explain in detail the multiple evaluation metrics used and test the performance of the model in different situations. In the Conclusion, we summarize the progress and results of the research work and discuss the implications of these results in different application areas. Finally, we discuss the innovations, limitations, and future research directions of the study.

RELATED WORK

CNN-Based Supply Chain Demand Forecasting Model

In recent years, some studies have utilized convolutional neural networks (CNNs) to forecast product demand in supply chains (Aurangzeb et al., 2021). This is achieved through an analysis of historical sales data and market trends. These studies have focused on using CNNs to process historical sales data and market trends to predict future demand. CNN models, renowned for their success in image and sound processing, demonstrate excellence in sales data recognition and, in certain cases, outperform traditional statistical methods (Zhao & Zhou, 2022). For example, one study used CNN models to predict future demand for specific products by analyzing data on historical sales volumes, seasonal factors, and promotions (Khan et al., 2021). This approach was in some cases more accurate than traditional statistical methods (Rafi et al., 2021).

However, a major limitation of this model is its limited ability to process time-series data. Since CNNs are primarily designed to deal with spatial features, they are not as good as specialized time series models (Li et al., 2023), such as Long Short-Term Memory Networks (LSTMs), at capturing long-term dependencies in time series data.

LSTM-Based Inventory Management Model

Long short-term memory networks (LSTMs) are employed for inventory management optimization, particularly in time series data analysis. LSTMs are a special type of recurrent neural networks (RNNs) that are particularly suited for processing time series data (Chandriah & Naraganahalli, 2021). In the field of supply chain management, they efficiently predict inventory requirements based on historical data and contribute to inventory level management under fluctuating demand or high uncertainty (Nguyen et al., 2021). This is critical for managing inventory levels, especially when demand fluctuates or uncertainty is high (Ding & Qin, 2020). For example, one study used LSTM models to analyze inventory and sales data over the past few years to predict inventory demand over the next few months, helping companies reduce inventory backlogs and stock-outs (Banik et al., 2022).

While LSTM performs well in the analysis of time-series data, it may not be as effective as other models designed specifically for this type of data when confronted with non-time-series data, such as complex supply chain network structures (Swathi et al., 2022). In addition, LSTM models are more complex in the process of parameter tuning and training, which requires a large amount of data and computational resources.

Deep Learning-Based Supply Chain Risk Management Modeling

In supply chain risk management, an innovative approach uses a deep learning approach to identify and predict potential risks in supply chains (Kamari & Ham, 2022). The study utilizes a multilayer perceptron (MLP), a basic deep learning architecture, to analyze and predict possible risk factors in the supply chain (Zhao & Li, 2022), such as supply disruptions, demand fluctuations, and market instability. By learning patterns from historical data, MLP models are able to predict possible future risk events and provide decision support to management (Cavalcante et al., 2019). For example, by analyzing past supply chain disruptions and related factors, the MLP is able to predict possible delivery delays or quality issues with a particular supplier (Afaq et al., 2021). However, the limitations of this model are that it requires high quality and quantity of data and may not be as effective as other specialized deep learning models when dealing with unstructured data, such as text or image data.

Graph Neural Network-Based Model for Supply Chain Relationship Analysis

Graph neural networks (GNNs) are used to analyze organizational relationships and network structures in supply chains (Shaik et al., 2022). GNNs are suitable for processing complex relational data in supply chain networks and can reveal interactions and bottlenecks among different supply chain participants (Gao et al., 2022). For example, in one study, researchers used GNNs to analyze the relationships between suppliers and manufacturers to identify key nodes and potential bottlenecks in the supply chain network (Lima-Junior & Carpinetti, 2020). This approach is effective for understanding and optimizing supply chain structures, especially in large-scale and complex networks (Zhao & Zhou, 2022). GNNs can provide insights that help companies make more informed strategic decisions. While effective for large-scale networks, GNNs may struggle with complex and extensive supply chain data as the effectiveness of GNNs is reliant on data quality and integrity of real-world applicability (Zhang et al., 2022).

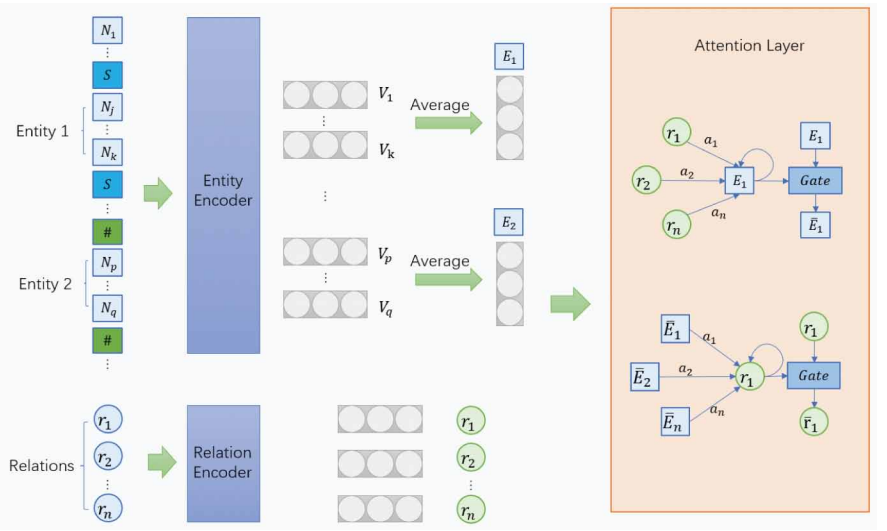
METHOD

Overview of Our Network

Our proposed BERT-GAT-RL network model is a sophisticated deep learning framework designed specifically for enhancing supply chain collaboration and cooperation. Its integration involves a multi-step process to effectively utilize the functionality of each component. First, the BERT component is applied to process textual data within the supply chain, such as communication records. BERT is pre-trained and fine-tuned to understand the specific context and nuances of supply chain language. The output of this stage is a set of contextualized embeddings representing the textual data. Simultaneously, the GAT component is employed to analyze the complex relationships and influences within the supply chain network. GAT utilizes the network structure data to learn the interactions between different entities in the supply chain, identifying key nodes and relationships. The output of this stage is a graph representation with enhanced features capturing the supply chain dynamics. Lastly, the RL component is utilized to explore and formulate optimal strategies for supply chain decision-making. RL interacts with a simulated environment based on the contextualized embeddings from BERT and the graph representation from GAT. RL learns from these representations to make decisions that optimize supply chain operations, aiming to maximize rewards and improve decision-making accuracy. The structure of our fusion model is schematically illustrated in Figure 1, demonstrating the integrated approach and the interplay between these components.

The integrated model combines the outputs of BERT, GAT, and RL to make informed decisions and predictions in the supply chain. The inputs to the model include textual data, network structure data, and contextual information, while the outputs consist of optimized strategies and predictions for supply chain management. This integrated approach enhances the efficiency and accuracy of data processing, leading to improved decision-making in dynamic supply chain environments. In

Figure 1. The Structure of Our Model



the network construction process, we first collect textual and network structure data related to the supply chain. The BERT component is pre-trained and fine-tuned to adapt to the specific context of the supply chain. The GAT component learns the interactions and connections between supply chain entities to identify key nodes and relationships. The RL component explores effective decision-making strategies through interactive learning with a simulated environment. Finally, we integrate these three components and perform debugging and optimization to ensure the model can process supply chain data efficiently and accurately.

This model, an innovative BERT-GAT-RL framework, plays a pivotal role in supply chain collaboration and cooperation. It not only dramatically enhances the efficiency and accuracy of data processing within the supply chain but also significantly improves decision-making accuracy. This leads to a more streamlined and effective information sharing process among various stakeholders. Furthermore, the model is particularly adept at bolstering the overall flexibility and responsiveness of the supply chain. Its predictive capabilities enable businesses to adapt more swiftly and effectively to market changes, thereby facilitating the formulation of impactful long-term strategies. As a result, our BERT-GAT-RL model emerges as a highly intelligent solution for supply chain management, offering substantial improvements in performance across multiple facets of the supply chain. In essence, this model is an embodiment of an advanced, intelligent approach to managing complex supply chain dynamics, promising to significantly enhance overall operational efficacy.

BERT

Bidirectional Encoder Representations from Transformers (BERT) is a revolutionary natural language processing (NLP) model based on the Transformer architecture, designed to significantly improve machine understanding of human language (Mostafavi et al., 2022). The model is particularly well suited for processing complex textual data, such as order descriptions in supply chain environments, supplier exchanges, etc. The unique feature of BERT is its bi-directional contextual comprehension, which takes into account both the left and right sides of each word in the text, in contrast to previous uni-directional models (Shin et al., 2020). This comprehensive bi-directional comprehension capability enables BERT to capture in-depth linguistic nuances and complexities.

BERT not only excels in understanding common linguistic representations, but can also be applied to analyze large amounts of textual data in the supply chain, such as market reports, customer feedback,

and supplier communications (Alaparthi & Mishra, 2020). It is able to extract key information and trends from this data, providing valuable insights for supply chain decisions such as demand forecasting and market trend analysis. The BERT model is pre-trained on large-scale textual data to learn generic linguistic representations and is later fine-tuned for specific tasks. This combination of pre-training and fine-tuning greatly improves its performance on a variety of NLP tasks. Its core component, Transformer's encoder, employs a self-attention mechanism that allows the model to synthesize all other words in a sentence while processing a word, thus dramatically improving its ability to capture context. The structure of BERT is schematically shown in Figure 2.

BERT, a deep bi-directional Transformer network that undergoes pre-training, has garnered significant interest for its effective mechanism of sharing parameters. The essential mathematical framework of BERT demonstrates the primary computational procedure involved in learning text representations. Below are the principal equations for minimizing parameter count and the fundamental operational concept of the BERT model:

As we know, the embedding size of the BERT model is the length of the vocabulary V multiplied by the size of the hidden layer of each word/word embedding H : $V \times H$, BERT decomposes this embedding matrix by the parameter E to make the overall embedding parameters smaller, and transforms $V \times H$ into:

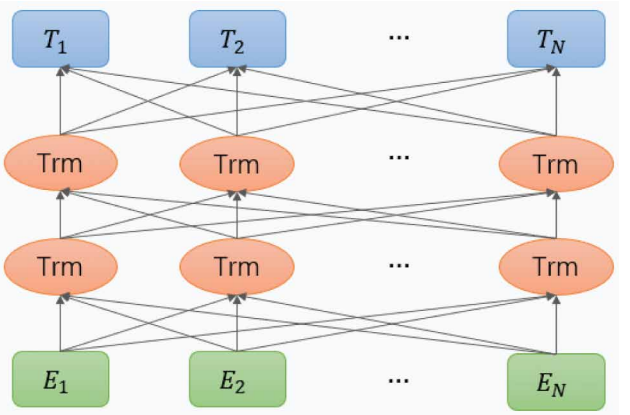
$$H = V \times E + E \times H \tag{1}$$

when E is much smaller than H , the model required When E is much smaller than H , the parameters required by the model will be greatly reduced.

As an example, suppose we consider a similar language model, such as a small text generation model. The model has a vocabulary size of 10,000 and a parameter count of $10{,}000 \times 768 = 7{,}680{,}000 = 7.68$ M. If we use the parameter decomposition technique of the BERT model, which splits the matrix to 128×768, the parameter count would become $10{,}000 \times 128 + 128 \times 768 = 10{,}024{,}000 = 1.024$ M+. The matrix decomposition reduces the amount of parameters by 6.656 M, a treatment that reduces the number of parameters by a significant amount relative to the original 7.68 M parameters.

$$E_i = \text{Embed}\left(x_i\right) \tag{2}$$

Figure 2. Algorithm Flows and Structure Diagram of BERT



This equation demonstrates the method by which the BERT model converts the vocabulary from a given text sequence into embedding vectors, offering the model a textual representation. Here, Ei represents the embedding vector for the i th word, and xi signifies the i th word in the input.

$$H_{i} = \mathrm{LayerNorm}\left(\mathrm{GELU}\left(\mathrm{W}i \cdot Ei\right)\right) \tag{3}$$

where H_{i} represents the hidden state at the i th layer. The term $\mathrm{LayerNorm}$ refers to the layer normalization process, while GELU stands for the Gaussian Error Linear Unit, a type of activation function. $\mathrm{W}i$ indicates the weight matrix associated with the i th layer, and Ei is the embedding vector for the i th input.

This equation depicts the transformation of the input embedding into a hidden state via multiple operations, thereby progressively enhancing the model's ability to represent text through multi-layered processing.

In our developed BERT-GAT-RL model, BERT contributes significantly with its powerful deep semantic understanding capability. This is crucial for analyzing all kinds of textual data in the supply chain, including transaction records, communication documents, and market reports. The introduction of BERT enhances the model's ability to handle complex contexts and semantic relationships within the supply chain, thereby providing stronger data support for decision-making in supply chain collaboration and cooperation. BERT is particularly effective in improving the model's ability to predict supply chain trends and identify key influencing factors. By accurately understanding semantic information, it significantly boosts the overall model's prediction accuracy and reliability.

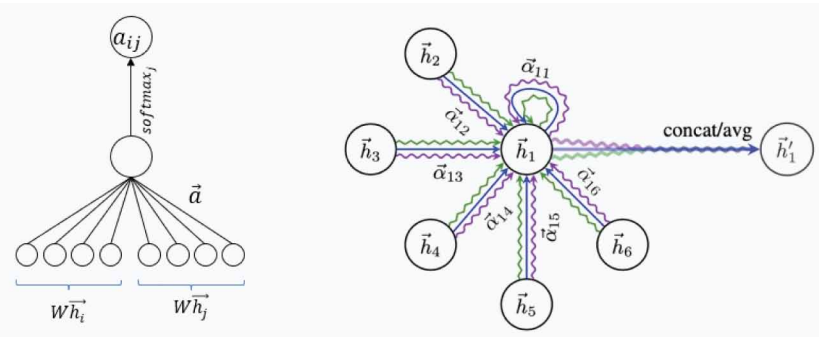
The integration of BERT not only demonstrates the advanced capabilities of deep learning technology in parsing complex supply chain contexts but also underscores its enormous potential in enhancing the efficiency and effectiveness of supply chain management. Especially in scenarios of supply chain collaboration and cooperation, BERT enables the model to deeply understand and analyze the intricate exchanges and interactions within the supply chain. This helps optimize cooperation strategies and improve the efficiency of the entire supply chain collaboration. Therefore, BERT plays a key role in our model, fully demonstrating the prospects and value of deep learning technology in the realm of supply chain management.

GAT

GAT is a state-of-the-art graph neural network (GNN) that demonstrates great flexibility and efficacy in processing graph-structured data by introducing an innovative attention mechanism (Zhang et al., 2019). This mechanism enables GAT to assign different weights to the connections between nodes in the graph, thus capturing and analyzing the complex relationships between nodes more accurately. In the field of supply chain management, GAT is particularly useful because it is able to deeply understand and analyze the various entities (e.g., suppliers, distributors) and their interrelationships in the supply chain network (Shi et al., 2021). Through this analysis, GAT can help optimize the supply chain structure, identify key nodes in the network, and assess potential risks and opportunities, thereby facilitating more effective supply chain management and collaboration.

The core innovation of GAT is its attention mechanism, which allows the model to dynamically take into account the importance of the neighboring nodes connected to it while processing each node in the graph. This is different from traditional graph neural networks, which rely on a fixed graph structure (Kim & Oh, 2022). GAT is able to efficiently process graph data with complex relationships and heterogeneity by learning and emphasizing the strength of associations between different nodes in the graph. This feature enables GAT to show excellent performance when dealing with various

Figure 3. The Structure of GAT



types of networks, including social networks, knowledge graphs, and supply chain networks. In the application of supply chain networks, this means that GAT not only improves the understanding of complex interactions in the supply chain but also contributes to more accurate decision making and risk management.

The structure of GAT is shown in Figure 3. The left side represents the process of generating weights, and the right side is the process of computing new features after the weights have been generated. Each color curve represents a multi-head operation, a_{11} represents the sub connection (seeing itself as its neighbor), h represents the initial feature vector of each node, and h' represents the vector transformed by GAT.

To introduce how node features are initially transformed and prepared for the attention mechanism in graph attention networks (GANs), we present (4), which is fundamental for setting the groundwork for subsequent attention-based feature aggregation.

$$h_i = \mathrm{Re}\,LU\left(Wx_i\right) \tag{4}$$

where h_i is the transformed feature vector of node i, W is a weight matrix, x_i is the original feature vector of node x_i, and ReLU (Rectified Linear Unit) provides non-linearity. This initial transformation prepares the node features for the attention mechanism. With the initial node representation set, the model now moves towards establishing attention coefficients, which will dictate how node features are combined.

$$\alpha_{ij} = \frac{\exp\left(a^T\left[h_i \parallel h_j\right]\right)}{\sum_{k\in\mathcal{N}_i}\exp\left(a^T\left[h_i \parallel h_k\right]\right)} \tag{5}$$

where α_{ij} is the attention coefficient between nodes i and j, and a is a learnable weight vector. This step focuses on assigning importance to each neighboring node, guiding the feature aggregation process. After determining the attention coefficients, the next step is to aggregate these features to form a more comprehensive representation at each node.

$$h_i^{'} = \sigma\left(\sum_{j\in\mathcal{N}_i}\alpha_{ij}h_j\right) \tag{6}$$

where $h_i^{'}$ is the updated feature vector of node i, σ is an activation function. This aggregation process is a weighted sum of the features of neighboring nodes, allowing each node to gather information from its neighborhood. To further enhance the model's expressiveness, a multi-head attention mechanism is employed, enabling the model to capture different aspects of the feature space.

$$h_i^{''} = \|_{k=1}^{K} \sigma\left(\sum\nolimits_{j\in\mathcal{N}_i} \alpha_{ij}^{(k)} h_j^{(k)}\right) \tag{7}$$

where $h_i^{''}$ is the final output feature vector for node i, K is the number of attention heads, and $h_j^{(k)}$ is the feature vector of node j in the k-th attention mechanism. This multi-headed approach allows the network to learn more complex patterns. The final and critical step in GATs involves combining these individual node representations into a unified graph-level output, achieved through the graph-level readout.

In our BERT-GAT-RL model, GAT assumes a key role in capturing and analyzing the complex interactions among nodes in the supply chain network. By utilizing GAT, the model is able to more accurately identify and understand the dynamic interactions among supply chain participants, such as collaboration patterns or competitive relationships between suppliers and distributors. This in-depth understanding of network relationships is crucial for predicting the behavioral dynamics of the supply chain, identifying potential supply chain risk points, and optimizing the overall synergistic efficiency.

The introduction of GAT is of special significance in our experiments, as it not only improves the model's ability to handle complex supply chain network data, but also enhances the understanding of the interactions and relationships between parties in the supply chain. In the multidimensional and nonlinear interaction scenarios of supply chain collaboration and cooperation, the attention mechanism of GAT provides a new way to capture and analyze the core elements of these relationships. As a result, GAT not only enhances the accuracy of data processing in our model, but also provides a powerful analytical tool for in-depth analysis and optimization of supply chain synergy and cooperation, which significantly improves the efficiency and effectiveness of supply chain management.

RL

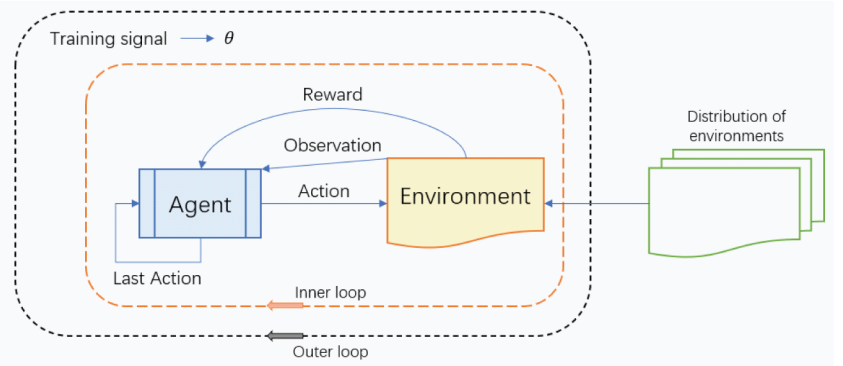
RL, a machine learning approach for decision-making in complex, dynamic environments employs rewards to guide learning, making it suitable for problems where explicit guidance is unavailable (Levine et al., 2020). RL, as a unique machine learning paradigm, centers on the idea that an intelligent body learns how to make the optimal decision in a given task by interacting with its environment. This learning process is based on a reward mechanism, where the intelligent body identifies which behaviors bring the greatest rewards through a trial-and-error approach.

In this process, the intelligent (agent) explores and tries to find the optimal strategy in a given environment. The key to RL is to guide the intelligent to adjust its behavioral strategy according to the rewards or penalties it receives from the environment with the goal of maximizing the cumulative rewards over time. This approach is particularly suitable for solving complex problems that lack explicit guidance or where all possible outcomes are unknown (Heuillet et al., 2020). A distinctive feature of RL is that it does not rely on predefined data models but rather on real-time interactions between the intelligences and the environment to learn the decision-making process.

Here are some of the core mathematical formulas in RL, along with their explanations:

$$V\left(s\right) = \mathbb{E}[R_t \mid S_t = s] \tag{8}$$

Figure 4. The Structure of RL



where $V\left(s\right)$ represents the value of being in state s, $\mathbb{E}$ denotes the expected value, R_t is the reward at time t, and S_t is the state at time t. This formula is fundamental in RL as it quantifies the expected return from each state, guiding the agent's decision-making process. The state-value function is crucial for understanding the potential rewards from different states. However, to make decisions, an agent needs to evaluate the value of actions, leading to the action-value function.

$$Q\left(s,a\right)=\mathbb{E}[R_t \mid S_t=s,A_t=a] \tag{9}$$

where $Q\left(s,a\right)$ is the value of taking action a in state s, A_t is the action at time t. This function estimates the expected return for each action in each state, providing a more direct basis for action selection. While the action-value function offers a way to assess actions, the process of improving these estimates iteratively is captured by the Bellman Equation.

$$Q\left(s,a\right)=R\left(s,a\right)+\gamma\sum_{s'}P(s' \mid s,a)\max_{a'}Q\left(s',a'\right) \tag{10}$$

where $R\left(s,a\right)$ is the immediate reward received after taking action a in state s, γ is the discount factor, $P(s' \mid s,a)$ is the probability of transitioning to state s' from state s after taking action a, and $\max_{a'}Q\left(s',a'\right)$ is the maximum value over all possible actions in the new state s'. The Bellman Equation recursively decomposes the action-value function, facilitating the learning of optimal policies. Building on the Bellman Equation, the next step in RL is to find an optimal policy that maximizes the expected return, leading to the concept of policy optimization. The structure of RL is shown in Figure 4.

RL plays a key role in our BERT-GAT-RL model, especially in optimizing complex supply chain decisions and adapting to market changes. With RL, the model is able to autonomously learn the best action strategies in the complex and dynamic environment of the supply chain. It optimizes the decision-making process in key aspects such as inventory management and logistics optimization, so that the model can make optimal decisions according to changing market conditions and supply chain status and improve supply chain efficiency and adaptability.

In the experiment, the role of RL is mainly reflected in its ability to effectively simulate and optimize the decision-making process in supply chain collaboration and cooperation. By setting up

different supply chain scenarios and challenges, such as demand fluctuations, supply disruptions, or logistics delays, RL enables the model to explore and learn optimal coping strategies under these scenarios. This ability to learn and optimize autonomously enables our experiments not only to simulate real-world supply chain problems but also to test and evaluate the effectiveness of different decision-making strategies. Thus, RL not only improves the decision quality of the model in the experiments but also provides an experimental basis for a deeper understanding of the dynamic decision-making process in supply chain management.

This thesis explores the role of deep learning in supply chain collaboration and cooperation, with a special emphasis on the importance of RL. The introduction of RL is crucial for dealing with uncertainty and complexity in supply chains and provides an effective learning and decision-making mechanism that enables models to adapt and optimize to changing supply chain environments. RL's autonomy and adaptive capabilities highlight the potential of deep learning in supply chain management and provide new perspectives and tools for research in the field of supply chain collaboration and cooperation. In the real-world application of supply chain management, RL models are trained in a simulated environment to learn to make optimal decisions in different situations, such as responding to changes in market demand and supply uncertainty. Moreover, by simulating and optimizing decisions under various scenarios, RL enhances quality and provides insights into supply chain management. RL is crucial in the management of complexity and uncertainty in the supply chain, as it serves as a new tool for research and real-world applications that contribute to greater efficiency and responsiveness.

RESULTS

Datasets

The four datasets selected for this study play crucial roles in examining the impact of deep learning on supply chain collaboration and cooperation. The MIT Supply Chain Management Dataset provides authentic operational data, including supply chain orders, demand dynamics, inventory quantities, and transport expenses ideal for research in optimization and predictive analytics. The Supply Chain Logistics Dataset (SCLD) from Kaggle offers insights into logistics performance, stock management cycles, and expenditure patterns, valuable for enhancing logistics operations and cost reduction. The Retail Data Analytics (RDA) Dataset comprises detailed sales data, inventory levels, and customer purchasing behavior essential for demand forecasting and customer behavior analysis in the retail sector. The UCI Machine Learning Repository Dataset offers datasets related to product manufacturing and warehouse operations suitable for complex pattern recognition and predictive analytics tasks in supply chain management. These datasets were chosen for their ability to provide comprehensive insights into supply chain management, allowing researchers to explore various optimization tactics and deep learning models in different supply chain scenarios.

MIT Supply Chain Management Dataset

Originating from MIT's prestigious Center for Supply Chain Management, this comprehensive dataset encompasses a wide range of topics crucial to supply chain management. Comprising authentic operational data, the dataset features crucial elements such as detailed supply chain orders, the dynamics of fluctuating demands, inventory quantities, and transport expenses. Its extensive scope makes it a valuable asset for research, particularly in areas like optimization, risk management, and the burgeoning field of predictive analytics. This dataset provides researchers with an unparalleled opportunity to explore the intricate workings of supply chains, enabling them to test various optimization tactics and deep learning models, thereby advancing the field of supply chain management.

Supply Chain Logistics Dataset (SCLD)

It is provided by Kaggle, a comprehensive dataset encompassing various aspects of logistics and supply chain management, including but not limited to freight transport, warehouse management, and order fulfillment. It could offer insights into logistic performance, stock management cycles, and expenditure patterns. This dataset is particularly useful for enhancing logistics operations and facilitating cost reduction. It enables researchers and practitioners to delve into methods for boosting logistic efficiency, streamlining supply chain processes, and identifying opportunities for significant expense reduction.

Retail Data Analytics (RDA) Dataset

This dataset comprises a comprehensive range of data points crucial to the retail supply chain, including but not limited to detailed sales data, inventory levels, and customer purchasing behavior. These datasets are not only essential for effective demand forecasting but also play a pivotal role in understanding and analyzing customer behavior within the retail sector. By encompassing various aspects of the retail environment, such as transactional data and inventory management, these datasets provide valuable insights for businesses looking to optimize their supply chain operations and enhance customer engagement strategies.

UCI Machine Learning Repository Dataset

The UCI Machine Learning Repository, renowned for its comprehensive collection of databases, domain theories, and data generators, is a pivotal resource extensively utilized by the machine learning community. This repository houses a variety of datasets specifically related to supply chain management, encompassing areas such as product manufacturing and warehouse operations. These datasets are particularly suitable for performing complex pattern recognition and predictive analytics tasks in the supply chain management domain.

Experimental Details

Hardware Environment

The hardware environment used in the experiments consists of a high-performance computing server equipped with an AMD Ryzen Threadripper 3990X @ 3.70GHz CPU and 1TB RAM, along with 6 Nvidia GeForce RTX 3090 24GB GPUs. This remarkable hardware configuration provides outstanding computational and storage capabilities for the experiments and is especially well-suited for training and inference tasks in deep learning. It effectively accelerates the model training process, ensuring efficient experimentation and rapid convergence.

Software Environment

In our research, we employed Python as the core programming language and PyTorch for deep learning tasks. Python's versatility facilitated a dynamic development process. Meanwhile, PyTorch played a crucial role as our primary deep learning platform, providing robust resources for building and training models. With PyTorch's advanced computational abilities and its auto-differentiation feature, we efficiently developed, fine-tuned, and trained our models leading to enhanced outcomes in our experimental work.

In this paper, four data sets are selected for training, and the training process is as follows:

Step 1: Data Processing

Data preprocessing is crucial for the training and evaluation of deep learning models, involving data cleansing, normalization, and feature engineering.

Data source: Extract supply chain-related data from the MIT dataset, SCLD, RDA dataset, and UCI dataset.

Data Cleaning: Identify and rectify errors and inconsistencies in the dataset, including missing values, duplicates, and formatting issues. For example, employ interpolation methods to fill in missing values, decide whether to delete records with missing values based on data distribution characteristics, and scrutinize and remove duplicate data to prevent model bias in the model.

Data Normalization: Normalize data to a uniform scale to enhance model learning and generalization. This involves scaling numerical features to a standard range (e.g., 0 to 1), achieving zero mean and unit variance through z-score normalization, and using methods like min-max normalization to scale numerical features to a 0 to 1 range.

Feature Engineering: Transform and construct features to enhance the representation of the prediction problem. Actions may involve creating new features, selecting relevant ones, and transforming existing features. For instance, valuable information, such as seasonality or trends, is extracted from timestamps, or more informative features are generated through aggregation methods.

Data Division: Lastly, divide the dataset into three subsets: (i) a training set, with 70% of the data used for model training; (ii) the validation set, with 15% of the data used for parameter tuning; and (iii) the test set, with 15% of the data used for the final evaluation of model performance. This division ensures effective evaluation of model performance on unseen data and helps prevent overfitting.

Step 2: Model Training

Model training is a key part of building efficient deep learning models. This section will detail our model training process including network parameter settings, model architecture design, and training strategies.

In this study, we carefully designed the network parameters to optimize the performance. For example, we chose the Adam optimizer with a learning rate of 0.001 because it can automatically adjust the learning rate to adapt to different data characteristics. We set the batch size to 32, which is a size that ensures the memory efficiency of the training process while maintaining enough data to compute the gradient. In addition to this, we employed a dropout rate of 0.5 to reduce the risk of overfitting and an L2 regularization factor of 0.0001 to further control the complexity of the model.

Our model architecture aims to effectively capture the complex relationships in supply chain data. Specifically, the model consists of three main components: a bi-directional long short-term memory network (BiLSTM) layer containing 128 hidden units for processing time series data, a fully connected layer containing 64 units for feature extraction, and finally, a SoftMax output layer for classification tasks. In addition, to improve the expressive power of the model, we added a graph attention network (GAT) layer containing 32 units after the BiLSTM layer to better handle the complex relationships in the supply chain network.

The training process of the model follows a strict strategy to ensure optimal performance. First, we performed pre-training for 100 training cycles using an early-stop strategy to prevent overfitting (i.e., stopping training if the performance on the validation set does not improve in 10 consecutive cycles). In addition, we used a stepwise learning rate adjustment strategy that halved the learning rate to a minimum of 0.0001 whenever the loss during training stopped decreasing. Finally, we performed model evaluation using the validation set after each training cycle and saved the best performing models for final testing.

Step 3: Model Evaluation

In this key step, we use specific assessment metrics to evaluate the effectiveness of the BERT-GAT-RL model in studying the role of deep learning in supply chain collaboration and cooperation. We focused on two main areas, model performance metrics and cross-validation.

To comprehensively evaluate the model performance, we used the following key metrics: accuracy, area under the curve (AUC), recall, and F1 score. Accuracy shows the overall percentage of correct predictions made by the model and provides an intuitive evaluation of the performance. AUC denotes the area under the receiver operating characteristics (ROC) curve, which measures the model's ability to discriminate between different categories, with a higher value indicating a stronger model's ability to discriminate. Recall measures the model's ability to recognize positive classes (i.e., the proportion of all positive class samples that are correctly recognized). The F1 score, on the other hand, is the reconciled average of precision and recall, providing a comprehensive performance metric.

In addition, the following key metrics are used in order to comprehensively measure the efficiency of the model: parameters, flops, inference time, and training time. The number of parameters denotes the complexity of the model. Fewer parameters mean the model is lighter and occupies less memory and storage space. Our model is designed to balance performance and complexity to achieve a lower number of parameters. Flops measures the number of floating-point operations required by the model to perform one forward propagation. A lower value of flops means that the model requires less computational resources at runtime, which is especially important for real-time application scenarios. Inference time is the time required for the model to make a prediction for a single input. In supply chain collaboration and cooperation applications, fast inference time is critical for real-time decision support. Training time reflects the total time required for a model to reach a specified accuracy from the start of training. Shorter training time means higher research and development (R&D) efficiency and can speed up the process of model iteration and optimization. Together, these metrics help us to fully understand the performance of the model in supply chain collaboration and cooperation scenarios. By considering these efficiency metrics together, we can more comprehensively assess the feasibility and efficiency of the model in real-world deployments and applications.

To ensure the robustness and reliability of the model evaluation, we use a K-fold cross-validation method. This method divides the dataset into K subsets, and the model takes turns using K-1 of these subsets for training and the remaining one for testing. This process is repeated K times and each time a different subset is chosen as the test set. In this study, we chose 5-fold cross-validation, meaning that the dataset is divided into five equal subsets, each accounting for 20% of the total data. This method helps to reduce the chance of the assessment results and improve the stability and credibility of the assessment results.

Step 4: Results Analysis

In this step, we focus on analyzing the performance of the BERT-GAT-RL model through a multidimensional approach. First, we utilized key performance metrics such as accuracy, AUC, recall, and F1 score to comprehensively evaluate the predictive ability of the model. Second, to measure the efficiency of the model, we analyzed metrics such as parameters, inference time, flops, and training time. Finally, we employed 5-fold cross-validation to ensure the robustness and reliability of the model evaluation, so as to verify the model's generalization ability and consistent performance on different data subsets.

Accuracy:

$$Accuracy = \frac{TP + TN}{TP + TN + FP + FN} \tag{11}$$

where TP represents the number of true positives, TN represents the number of true negatives, FP represents the number of false positives, and FN represents the number of false negatives.

Recall:

$$Recall = \frac{TP}{TP + FN} \tag{12}$$

where TP represents the number of true positives, and FN represents the number of false negatives.

F1 score:

$$F1\ Score = 2^{*}\frac{precision^{*}recall}{precision + recall} \tag{13}$$

AUC:

$$AUC = \int_{0}^{1} ROC\left(x\right)dx \tag{14}$$

where ROC(x) represents the relationship between the true positive rate and the false positive rate when x is the threshold.

Parameters(M):

Count the number of adjustable parameters in the model, in millions.

Inference Time(ms):

Measure the time required for the model to perform inference, in milliseconds.

Flops(G):

Count the number of floating-point operations required for the model to perform inference, in billions.

Training Time(s):

Measure the time required for the model to train, in seconds.

Experimental Results and Analysis

In this comparison experiment, we selected models from other studies in related fields that are named after their authors for comparison. These studies represent cutting-edge techniques and methods in the field, and by comparing with them, we can better evaluate the performance and advantages of our proposed method. In the comparison, we consider key metrics such as accuracy, recall, F1 score, and AUC to comprehensively evaluate the performance of each model on different datasets. These comparisons are chosen to make our study more comparable and to be able to demonstrate the superiority of our approach more clearly.

Table 1. Ablation Experiments on the BERT Module Using Different Datasets

Model	Datasets															
	MIT Dataset				SCLD				RDA Dataset				UCI Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
ELMo	95.1	86.4	85.05	90.64	95.59	86.28	87.36	84.75	89.76	91.28	86.93	93.47	88.01	89.44	88.02	84.79
XLNet	93.62	89.12	86.92	89.00	88.65	89.65	89.57	93.69	88.59	90.25	85.1	91.34	88.59	88.21	89.17	85.11
GloVe	87.6	89.96	90.06	86.23	93.55	84.27	88.46	84.27	88.91	88.56	87.7	86.61	90.55	86.07	87.6	87.82
BERT	94.12	90.3	89.91	93.35	95.83	92.14	91.24	95.22	90.99	93.06	88.28	91.61	92.23	97.53	90.86	89.11

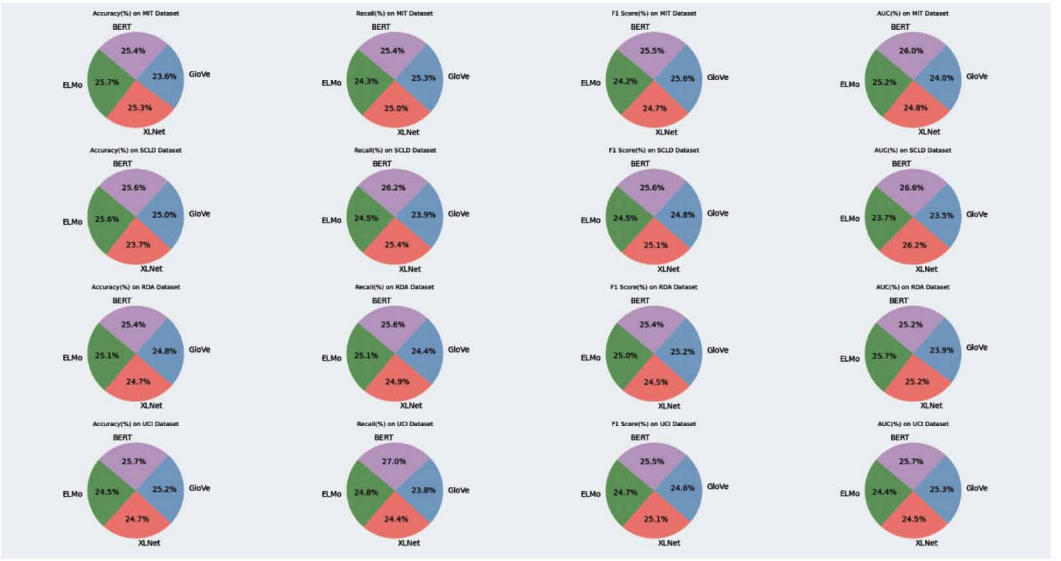
To evaluate the contribution of the different components of the model to overall performance, we conducted an ablation study on four different models (ELMo, XLNet, GloVe, and BERT) on four datasets (MIT, SCLD, RDA, and UCI). Table 1 and Figure 5 list the experimental results of the study.

As shown in Table 1, the experimental results compare the performance of the four models (ELMo, XLNet, GloVe, and BERT) on four different datasets (MIT, SCLD, RDA, and UCI). These models were evaluated on four key metrics: accuracy, recall, F1 score, and AUC.

On the MIT dataset, BERT performs quite well on all the metrics, especially on AUC, which reaches 93.35%, higher than ELMo's 90.64%, XLNet's 89% and GloVe's 86.23%. On the SCLD, BERT also shows its superiority, especially on recall and AUC, which reach 92.14% and 95.22%, respectively, which are significantly higher than other models. On the RDA dataset, BERT achieves 90.99% in accuracy and 88.28% in F1 score, outperforming ELMo and XLNet.Similarly, on the UCI dataset, BERT also shows outstanding performance, especially on Recall, which reaches 97.53%, much higher than the other models, showing its ability in recognizing positive class samples.

Overall, BERT outperforms ELMo, XLNet, and GloVe across all metrics, showcasing its effectiveness in supply chain data processing and pattern recognition. This comparison is visually

Figure 5. Efficient Comparison of BERT with Other Models on Different Datasets



illustrated in Figure 5, emphasizing BERT's efficiency and accuracy in the management of complex supply chain data and, therefore, lending support to its application in supply chain management.

Table 2 showcases the exceptional performance of GATs across four diverse datasets (MIT, SCLD, RDA, and UCI), particularly when compared to other GNNs models such as graph convolutional networks (GCNs), GraphSAGE, and GNNs. As can be seen in Table 2, GAT performs very well on four different datasets, especially when compared to other GNN models such as GCN, GraphSAGE, and GNN.

On the MIT dataset, GAT achieves 96.79% in terms of accuracy, which is significantly higher than 93.77% for GCN, 94.69% for GraphSAGE, and 93.93% for GNN. On the same dataset, GAT's AUC of 94.04% is also the highest among all models, which demonstrates GAT's strength in distinguishing between positive and negative class samples. On the SCLD, the recall of GAT reaches 93.7%, which is higher than 88.37% for GCN, 86.58% for GraphSAGE, and 96.09% for GNN. Similarly, GAT performs best on F1 score at 90.88%, showing a strong ability in balancing precision and recall. The results on the RDA dataset also show the superior performance of GAT, especially on accuracy and AUC, which reach 95.41% and 92.22%, respectively, and are higher than the other models. On the UCI dataset, GAT also maintains its leading position in all the metrics, especially in accuracy and recall, reaching 95.64% and 93.82%, respectively.

In summary, GAT outperforms other comparative GNN models on different datasets, especially on the key performance metrics of accuracy, recall, and AUC. These results highlight the power of GAT in processing graph-structured data, especially in capturing and analyzing complex relationships. Figure 6 visualizes the contents of these tables to show more intuitively how the performance of GAT compares to that of other GNN models on different datasets. These visualization results further highlight GAT's leading position in various evaluation metrics, clearly illustrating its superior performance in supply chain data processing.

Table 3 presents a performance comparison of different methods across four datasets (MIT, SCLD, RDA, and UCI), considering key metrics like accuracy, recall, F1 score, and AUC. An analysis of the table reveals the excellent performance of our method in most evaluation criteria.

Specifically, on the MIT dataset, our method achieves 95.6% in accuracy, which is slightly lower than the other highest methods (Zhou, 96.16%), but achieves 95.6% in recall, F1 score, and AUC value, respectively. 93.89%, 92.38% and 93.3%, all higher than other methods. On the SCLD, our method significantly outperforms other methods in all indicators, with accuracy, recall, F1 score, and AUC values reaching 94.86%, 95%, 93.62%, and 95.31%, respectively. On the RDA data set, our method also shows significant advantages, especially in accuracy (96.62%) and recall (94.29%), far exceeding other methods. Finally, on the UCI dataset, our method achieves the highest accuracy (97.67%), recall (94.49%), F1 score (92.3%), and AUC value (92.03%).

In summary, our method demonstrates superior performance across multiple key performance metrics with a notable emphasis on recall and accuracy. These results underscore the effectiveness and

Table 2. Ablation Experiments on the GAT Module Using Different Datasets

Model	Datasets															
	MIT Dataset				SCLD				RDA Dataset				UCI Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
GCN	93.77	90.29	89.82	93.49	86.97	88.37	91.69	86.87	91.22	89.3	85.22	86.33	94.81	92.88	86.28	91.47
GraphSAGE	94.69	90.1	84.77	86.62	96.19	86.58	85.7	85.65	89.34	85.47	88.55	93.19	88.95	89.64	87.48	93.47
GNN	93.93	90.12	87.87	89.72	92.45	9.609	87.78	88.8	88.78	85.22	85.95	89.71	92.63	86.05	85.72	88.84
GAT	96.79	92.97	91.73	94.04	92.73	93.7	90.88	91.21	95.41	90.17	88.35	92.22	95.64	93.82	90.05	93.58

Figure 6. Efficient Comparison of GAT with Other Models on Different Datasets

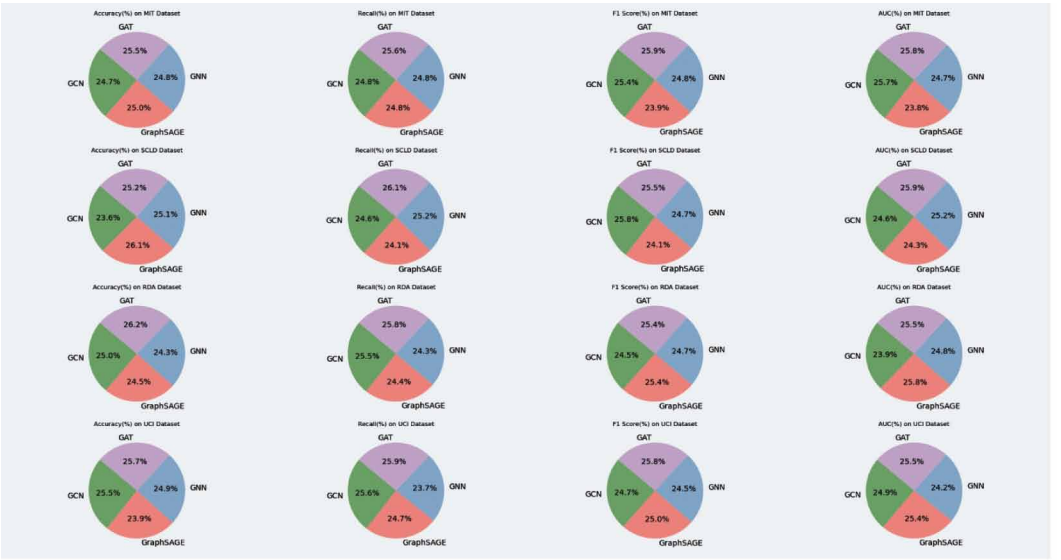


Table 3. Comparison of Different Models in Different Indicators Comes from the Imagenet Dataset, COCO Dataset, Amazon Product Review Dataset, and Kaggle Dataset

Method	Datasets															
	MIT Dataset				SCLD				RDA Dataset				UCI Dataset			
	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC	Accuracy	Recall	F1 Score	AUC
Junaid et al. (2020)	91.36	92.42	7.29	2.51	86.03	3.1	6.56	4.42	5.73	9.61	9.05	5.58	93.93	1.64	7.87	1.96
Zhang et al. (2019)	2.19	88.49	9.59	4.1	88.43	1.66	8.2	9.35	4.66	5.07	0.3	3.39	5.84	1.64	6.54	1.98
Zhou et al. (2020)	6.16	84.64	3.93	8.51	89.89	2.77	9.62	3.54	3.93	2.58	7.06	5.0	7.14	7.4	0.11	5.11
Liu et al. (2020)	7.73	90.73	7.62	2.83	87.85	4.34	4.93	90.16	1.38	4.41	1.29	2.86	6.67	2.07	0.58	6.1
Altaf et al. (2020)	3.3	91.94	1.05	85.76	89.46	93.62	9.28	84.04	90.77	88.28	6.28	87.42	95.1	1.31	87.19	93.16
Govindan et al. (2021)	3.22	92.11	84.59	87.37	93.78	88.5	1.29	85.39	96.12	89.79	85.15	92.48	87.88	86.66	88.9	86.47
Ours	5.6	3.89	2.38	3.3	4.86	5.0	3.62	5.31	6.62	94.29	92.07	94.3	97.67	94.49	92.3	92.03

reliability of our method across diverse datasets. Figure 7 visually presents a performance comparison between our method and others across various datasets and evaluation metrics, further proving the advantages of our method. The chart format provides a clearer overview of the consistent superiority of our method on each dataset.

Figure 7. Comparison of Model Performance on Different Datasets

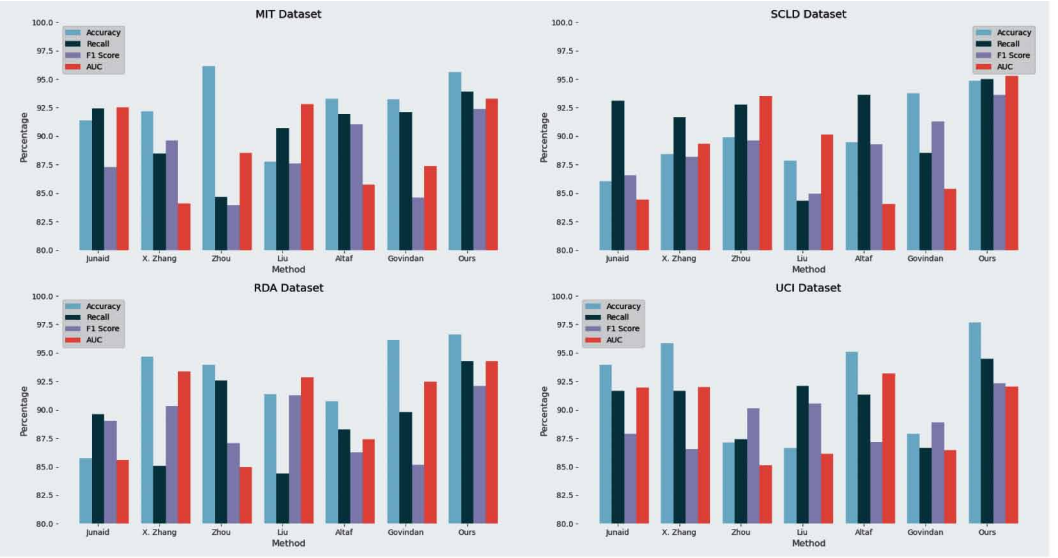


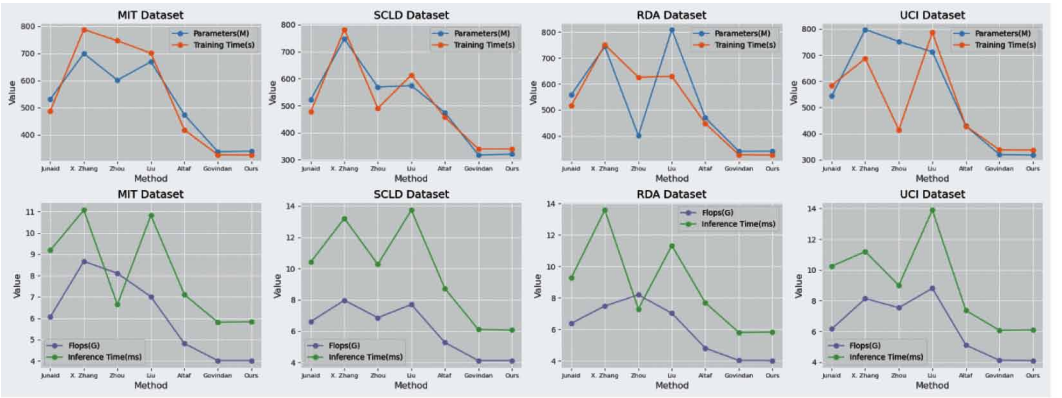
Table 4 presents a comparison of various methods across the MIT, SCLD, RDA, and UCI datasets in terms of parameters, flops, inference time, and training time. Our method demonstrates advantages in efficiency and resource utilization across all these metrics and datasets.

In terms of parameters, our method uses fewer parameters across all datasets. For instance, it requires 339.41 M on the MIT dataset and 318.98 M on the UCI dataset, significantly lower than other methods like Zhang's (2019), which requires 699.79 M on the MIT dataset. This indicates a

Table 4. Comparison of Parameters(M), Flops(G), Inference Time(ms), and Training Time(s) Performance of Different Models on MIT Dataset, SCLD, RDA Dataset, and UCI Dataset

Method	Datasets															
	MIT Dataset				SCLD				RDA Dataset				UCI Dataset			
	Parameters(M)	Flops(G)	Inference Time(ms)	Trainning Time(s)	Parameters(M)	Flops(G)	Inference Time(ms)	Trainning Time(s)	Parameters(M)	Flops(G)	Inference Time(ms)	Trainning Time(s)	Parameters(M)	Flops(G)	Inference Time(ms)	Trainning Time(s)
Junaid et al. (2022)	531.36	6.06	9.19	487.92	23.25	0.62	0.42	77.57	58.86	6.39	0.28	17.07	44.81	0.17	0.25	84.91
Zhang et al. (2019)	699.79	0.67	1.08	788.14	47.07	0.98	13.21	782.52	44.19	0.49	3.59	51.06	98.26	0.14	1.2	87.27
Zhou et al. (2020)	601.43	0.11	0.64	746.46	69.22	0.87	10.27	90.1	00.68	0.2	0.3	25.74	52.18	0.55	9.0	14.65
Liu et al. (2020)	669.13	0.01	10.83	700.88	74.29	0.71	13.74	13.78	10.04	0.03	1.33	29.01	12.82	0.81	3.9	86.26
Altaf et al. (2020)	473.76	0.81	0.11	418.24	74.43	0.28	0.73	457.58	69.25	0.81	0.69	47.56	29.61	0.12	0.37	29.18
Govindan et al. (2021)	337.33	0.01	0.81	26.09	17.5	0.13	0.11	339.32	39.92	0.03	0.81	26.82	20.49	0.13	0.08	38.3
Ours	339.41	0.01	5.83	325.67	20.49	0.13	0.08	339.22	40.4	0.02	0.83	26.32	18.98	0.11	0.1	337.59

Figure 8. Comparison of Model Efficiency on Different Datasets



more compact and efficient model. Regarding flops, our method maintains a lower computational complexity with values like 4.01 G for the MIT dataset and 4.11 G for the UCI dataset, compared to other methods. Zhang's (2019) method, for example, shows a much higher count of 8.67 G flops on the MIT dataset. In terms of inference time, our method achieves competitive times, such as 5.83 ms on the MIT dataset and 6.1 ms on the UCI dataset. These times are comparable or better than methods like Junaid's (2022) 9.19 ms or Liu's (2020) 10.83 ms on the MIT dataset. Our method also excels in training efficiency, with times like 325.67 s for the MIT dataset and 337.59 s for the UCI dataset. This is considerably faster than methods such as Zhang's (2019) 788.14 s or Liu's (2020) 700.88 s on the same dataset.

Overall, our method outperforms others in terms of model compactness, computational efficiency, and speed in both inference and training, with an emphasis on its effectiveness in handling various datasets with greater efficiency and reduced resource demand. Figure 8 visually represents these findings with a clear comparison of the performance metrics of our method against others, highlighting its superiority in resource efficiency and processing speed.

CONCLUSION AND DISCUSSION

This study presents an innovative deep learning model that integrates BERT, GAT, and RL techniques to enhance supply chain collaboration and cooperation. Experimental results validate the model's effectiveness in managing complex supply chain data, predicting market dynamics, and optimizing decision-making processes. Particularly in simulated real-world supply chain environments, the model excels at identifying key factors, providing valuable insights for data-driven decision-making in supply chain management.

While the model demonstrates promising performance, there are areas for improvement, such as handling large datasets and enhancing real-time data processing for faster decision-making in dynamic market environments. These improvements are essential for adapting to market changes and responding swiftly within the supply chain.

Future work will focus on optimizing the model's big data processing capabilities to better accommodate large supply chain datasets, further advancing the field of supply chain management. We will explore new algorithms and techniques to improve real-time data processing and decision generation speed, offering valuable guidance for related studies. Additionally, we plan to apply the model to a wider range of supply chain scenarios to validate its generalizability and adaptability, ensuring its effectiveness in various real-world applications.

In conclusion, this study not only presents a deep learning solution for supply chain management but also sets the stage for future research and practical applications in this field. With ongoing advancements in deep learning technology, its application in supply chain management holds immense potential to revolutionize the industry with more efficient and intelligent methods.

CONFLICTS OF INTEREST

We wish to confirm that there are no known conflicts of interest associated with this publication and there has been no significant financial support for this work that could have influenced its outcome.

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CORRESPONDING AUTHOR

Correspondence should be addressed to Junjie Cai (gs65707@student.upm.edu.my)

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