Intelligent Decision-Making Architecture Powered by Decision Transformer for Cross-Border E-Commerce Supply Chains

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ABSTRACT

This paper introduces an innovative demand forecasting framework for cross-border e-commerce supply chains, called Trans-Demand Net, specifically designed to address the complexity and uncertainty in demand forecasting for supply chain management. The framework seamlessly integrates the multi-head self-attention mechanism of the Transformer architecture to effectively capture long-term dependencies in time series data, while leveraging GCN to analyze the logistics network structure within the supply chain. Additionally, by incorporating the SAC reinforcement learning strategy, the model's adaptability and decision-making optimization are further enhanced. Experimental results on the Amazon Product Reviews Dataset and Alibaba B2B Transaction Dataset demonstrate that Trans-Demand Net significantly outperforms traditional forecasting models across multiple key performance metrics, including MAE, MSE, and RMSE. Through a series of ablation experiments, we further validate the positive contributions of each component within the framework to the overall model performance. Trans-Demand Net exhibits outstanding predictive accuracy and robustness in the dynamic environment of cross-border e-commerce supply chains, providing an innovative and effective solution for intelligent supply chain management.

Keywords: Deep learning, Cross-Border E-Commerce, Supply chain, Demand forecasting, Intelligent forecasting model, Transformer architecture, Supply chain optimization

1. Introduction

As a vital component of global trade, cross-border e-commerce is rapidly growing. However, the transaction processes involved in cross-border e-commerce are complex, encompassing various goods, frequent orders, and a global logistics network, which introduces new challenges for supply chain management [1]. Consequently, how to accurately predict demand and formulate appropriate supply chain strategies amidst dynamic market conditions and high uncertainties in logistics has become an urgent issue for businesses to address.

Traditional supply chain demand forecasting methods, such as rule-based models and conventional statistical approaches, often exhibit significant limitations when faced with massive amounts of data and diverse features [2]. These methods rely on predefined rules or simple linear relationships, making it difficult to fully uncover deep patterns and non-linear structures in the data, leading to insufficient prediction accuracy and adaptability [3]. With the advent of deep learning, research in the field of supply chain demand forecasting has undergone a profound transformation. Deep learning models excel at handling large-scale data, multimodal information (e.g., text, images, time series), and capturing complex non-linear relationships [4]. These technological advantages make deep learning an ideal solution for addressing the challenges in cross-border e-commerce demand forecasting [5]. Specifically, time series modeling techniques in deep learning can learn intricate temporal patterns from extensive historical data, while Graph Neural Networks (GNNs) efficiently handle graph-structured data in logistics networks, extracting complex relationships between nodes and edges. Additionally, deep reinforcement learning (DRL) offers superior adaptability and efficiency in responding to the uncertainties and dynamic changes in supply chain management through continuous optimization of decision-making strategies [6].

In light of these challenges, this paper proposes an innovative intelligent demand forecasting framework for cross-border e-commerce, Trans-Demand Net. Trans-Demand Net integrates the multi-head self-attention mechanism of the Transformer model to capture long-term dependencies and deep features from multimodal information in time series data. Additionally, it incorporates a Graph Convolutional Network (GCN) to effectively process the graph-structured data in supply chains, capturing the complex dependencies between nodes (such as warehouses, distribution centers, and ports). To further optimize forecasting strategies, this study employs the Soft Actor-Critic (SAC) algorithm, an advanced deep reinforcement learning approach, which enhances the stability and efficiency of decision-making by maximizing policy entropy, enabling the model to better handle uncertainties in supply chain management. This framework combines deep learning and reinforcement learning techniques, overcoming the limitations of traditional methods and offering the potential to improve demand forecasting accuracy and supply chain decision-making intelligence.

The contribution of this article is mainly reflected in three aspects:

1. It proposes Trans-Demand Net, an intelligent demand forecasting framework for cross-border e-commerce based on the Transformer model, effectively integrating multimodal data to achieve high-precision demand forecasting using deep learning techniques.

2. It utilizes Graph Convolutional Networks (GCNs) to process the complex structure of logistics networks, capturing the intricate dependencies between nodes in the supply chain, providing richer feature representations for demand forecasting.

3. It combines the Soft Actor-Critic (SAC) reinforcement learning algorithm to dynamically optimize forecasting strategies, improving the model’s adaptability and decision-making efficiency.

2. Literature Work

In the field of supply chain demand forecasting, deep learning methods have been widely applied in recent years, demonstrating significant advantages. Traditional demand forecasting methods often rely on time series models (such as ARIMA and SARIMA) and machine learning algorithms (such as Support Vector Machines and Random Forests) [7]. While these methods can capture linear patterns in historical data to some extent, they often struggle to handle the complex multimodal data and nonlinear relationships inherent in supply chains. Therefore, deep learning methods have been introduced to improve the accuracy and robustness of demand forecasting models [8].

The application of deep learning in time series demand forecasting has achieved promising results. Many studies have adopted deep learning models such as Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU) to address the challenges of long-term dependencies and nonlinear characteristics in supply chain demand forecasting. For example, some studies have used LSTM models to predict demand by incorporating historical sales data and macroeconomic indicators, demonstrating that LSTM can better capture long-term dependencies and complex relationships among multiple variables, thereby improving forecasting accuracy [9]. However, these methods still face challenges in integrating multimodal data, especially when dealing with graph-structured data (e.g., logistics networks) and unstructured data (e.g., text reviews), where traditional deep learning models like LSTM are less effective [10].

Convolutional Neural Networks (CNN) and Graph Neural Networks (GNN) have also been increasingly applied to supply chain demand forecasting due to their capability in extracting complex features. For instance, the application of Graph Convolutional Networks (GCN) in logistics networks can effectively extract spatial dependencies and path information between nodes (such as warehouses and distribution centers), thereby enhancing the performance of demand forecasting models [11]. Similarly, models based on multi-layer convolution can more effectively handle data features in the spatial dimension, such as sales regions and network relationships in different markets [12]. However, convolutional neural networks have limitations in handling long time-series data and complex dependencies, making it difficult to fully leverage the diverse features in supply chain data [13].

Reinforcement learning has also attracted attention in supply chain management, especially in optimizing dynamic decision-making and strategy selection. Studies have shown that reinforcement learning can be used to dynamically adjust inventory, logistics routing, and transportation strategies [14]. For example, the application of Deep Q-Network (DQN) and Proximal Policy Optimization (PPO) algorithms in supply chain strategy optimization can achieve adaptive adjustments in dynamic decision-making, thereby improving overall efficiency [15]. However, these methods typically require large amounts of training data and computational resources, and exhibit certain limitations in handling complex multimodal features [1,16].

Despite these advances, there are still key issues in the field of deep learning for supply chain demand forecasting. Current research often focuses on a single data type or model, lacking comprehensive utilization and unified modeling capabilities for multimodal data. Many models fail to adequately consider the complex network structure information in supply chains when dealing with time-series features, leading to limited forecasting performance. While existing reinforcement learning algorithms excel in strategy optimization, their stability and efficiency in complex dynamic environments still need improvement.

Therefore, the Trans-Demand Net model proposed in this paper addresses these challenges by integrating the multimodal data fusion capability of the Transformer model, the graph-structured feature extraction capability of GCN, and the strategy optimization capability of SAC reinforcement learning. This approach not only captures the complex dependencies in supply chains more accurately but also dynamically optimizes demand forecasting strategies, enhancing the model's adaptability and decision-making efficiency to better cope with the uncertainties and dynamic changes in cross-border e-commerce supply chains.

3. Methods

3.1 Overview of Our Network

The paper proposes the Trans-Demand Net architecture for intelligent demand forecasting in cross-border e-commerce supply chains, which combines the Transformer, Graph Convolutional Network (GCN), and Soft Actor-Critic (SAC) algorithms to achieve multimodal data fusion, feature extraction, and decision optimization. The model is designed to address the complex dependencies and uncertainties inherent in cross-border e-commerce supply chains, leveraging deep learning techniques to enhance the accuracy of demand forecasting and the efficiency of supply chain management.

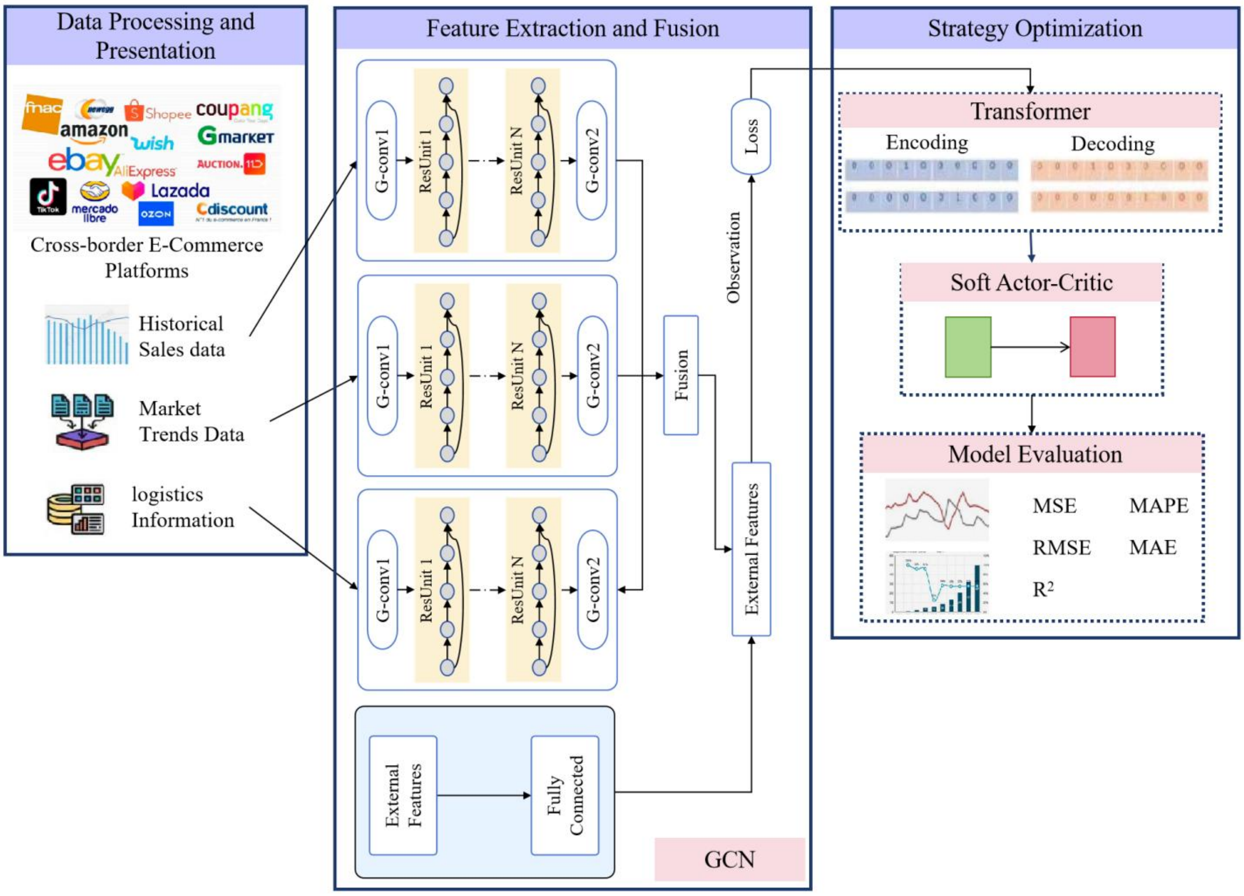

Figure 1. The LGB Model Architecture for Urban Green Space Change Detection. The model integrates a GCN for spatial data processing, focusing on trends, periods, and nearby information within urban regions. LSTM networks handle temporal data to capture dynamic trends in urban green space changes. The model uses G-conv1 and G-conv2 layers within the GCN for spatial feature extraction, supported by Residual Units (RestUnit) to maintain information flow. The Fusion component combines temporal and spatial features. The Bee Colony Algorithm optimizes the model parameters to enhance prediction accuracy. External features are included as additional data inputs to improve model performance.

As shown in Figure 1, the Trans-Demand Net overall architecture comprises three main modules: the Data Processing and Representation Module, the Feature Extraction and Fusion Module, and the Strategy Optimization and Decision-Making Module.

In the Data Processing and Representation Module, the system receives input data from multiple sources, such as historical sales data, market trends, logistics information, and external factors (e.g., exchange rate fluctuations, holiday impacts). To accommodate the requirements of multimodal data input, the data processing module performs preprocessing and standardization on different types of data. Text data is converted into usable vector representations through word embedding techniques, time-series data is processed using sliding windows and normalization techniques, and graph-structured data is represented as feature matrices of nodes and edges for subsequent modeling with the Graph Convolutional Network.

In the Feature Extraction and Fusion Module, the model employs GCN to process and learn from the graph-structured data of the logistics network. GCN captures the spatial dependencies and complex relationships between nodes in the supply chain (such as warehouses, distribution centers, and ports) by generating rich graph embeddings through multiple layers of convolution. These embeddings serve as node features that are input into the Transformer model to further integrate time-series data and other features. The Transformer model leverages its Multi-Head Self-Attention mechanism to handle temporal information and cross-modal features, capturing long-range dependencies and complex interactions in the data to generate high-dimensional, comprehensive feature representations. These representations encompass dynamically changing market demand, logistics network states, and other relevant factors within the supply chain, providing a solid foundation for subsequent strategy optimization.

In the Strategy Optimization and Decision-Making Module, SAC is used for the dynamic optimization of demand forecasting strategies. SAC, an advanced deep reinforcement learning algorithm, maximizes policy entropy to enhance exploration capability and decision stability. This module constructs the policy and value networks using the comprehensive feature representations generated by the Transformer and GCN. By continuously optimizing the forecasting strategy, the model dynamically adjusts decisions based on the real-time state of the supply chain, ultimately outputting optimal demand forecasting results and supply chain management recommendations, such as inventory replenishment strategies and logistics scheduling plans.

The overall architecture flow shown in Figure 1 demonstrates the interaction between modules and the flow of data. Data starts with multi-source input, undergoes standardization and feature construction in the processing and representation module, then is further processed by the deep learning capabilities in the feature extraction and fusion module, and finally enters the strategy optimization module to generate decision outputs. This design enables Trans-Demand Net** to efficiently handle complex supply chain data, achieve accurate demand forecasting, and optimize decision-making intelligently, providing a more competitive supply chain management solution for cross-border e-commerce enterprises.

3.2 Transformer module Module

In the Trans-Demand Net model, the Transformer component serves as a critical part primarily used for time series feature modeling and multimodal data fusion. Transformer excels in handling long-range dependencies and complex feature interactions [7]. Traditional recurrent neural networks such as LSTM and GRU can capture long-term dependencies in sequential data but often face problems like vanishing or exploding gradients when dealing with long sequences [8,14]. In contrast, the Transformer employs a self-attention mechanism that can more effectively capture global dependencies in data while supporting parallel computation, significantly improving training efficiency and predictive power.

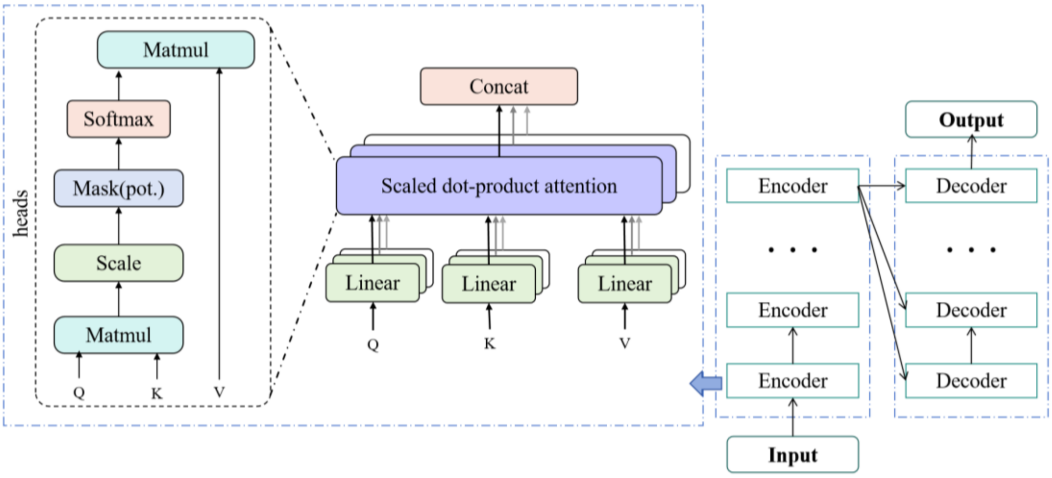

Figure 2. Transformer component network flow structure

As shown in Figure 2, the structure of the Transformer component includes modules such as Multi-Head Self-Attention, Positional Encoding, Encoder, and Decoder. In this component, the input data first passes through the multi-head self-attention layer, generating multiple different representations to help the model capture complex relationships and dependencies in the data. Positional encoding is used to preserve the temporal order of sequential data by embedding positional information into input features, aiding the Transformer in recognizing the time-series characteristics of the data. The encoder processes the input data through multiple layers of self-attention and feed-forward neural networks, while the decoder introduces a self-attention mechanism for the target sequence and cross-attention with the encoder output when generating predictive outputs for future demand.

The Transformer component adopts a Weighted Multi-Head Self-Attention mechanism to handle the weight distribution among multimodal data more effectively. For a given input sequence $\mathbf{X}=[x_1,x_2,\ldots,x_n]$, each input vector x_i is mapped into three sets of vectors: Query (Q), Key (K), and Value (V):

$$\mathbf{Q}=\mathbf{X}\mathbf{W}^{Q},\quad \mathbf{K}=\mathbf{X}\mathbf{W}^{K},\quad \mathbf{V}=\mathbf{X}\mathbf{W}^{V} \qquad \text{[Formular 1]}$$

where $\mathbf{W}^{Q},\mathbf{W}^{K},\mathbf{W}^{V}$ are the weight matrices. Based on this, a multimodal weighting factor α_m is introduced to accommodate differences among various data modalities, calculated as:

$$\alpha_m=\frac{\exp(\mathbf{q}_i\mathbf{k}_j^T/\sqrt{d_k})}{\sum_{j=1}^{n}\exp(\mathbf{q}_i\mathbf{k}_j^T/\sqrt{d_k})}\cdot\omega_m,\quad w_m=\frac{1}{1+\exp(-\mathbf{w}_m^T\mathbf{x})} \qquad \text{[Formular 2]}$$

where ω_m represents the weight parameter for the data modality, which is adjusted adaptively by learning the importance of the data, and w_m is the feature vector of the modality. The output of the weighted self-attention is:

$$\text{Weighted Attention}(\mathbf{Q},\mathbf{K},\mathbf{V})=\sum_{m=1}^{M}\alpha_m\mathbf{V} \qquad \text{[Formular 3]}$$

This formula ensures that the contributions of different modalities in the self-attention mechanism are dynamically adjusted, thereby improving flexibility and effectiveness in fusing multimodal data.

To capture dynamic changes in time-series data, the Transformer component introduces Dynamic Positional Encoding, which uses a transformed frequency encoding scheme, allowing position encoding to adapt to the time dimension. The formula for dynamic positional encoding is:

$$\mathbf{PE}(pos,t) = \sin\left(\frac{pos}{10000^{2t/d}}\right) + \phi(t), \quad \phi(t) = \gamma \cdot \log(t+1) \qquad \text{[Formular 4]}$$

where pos denotes the position, t represents the time step, $\phi(t)$ is the time variation function, and γ is the time adjustment factor. Dynamic positional encoding better adapts to the temporal characteristics of the data, enhancing the model's performance in dynamically changing environments.

To achieve efficient fusion of multimodal data, the Transformer component introduces a Fusion Embedding Transformation Layer, which embeds data from different modalities into a shared feature space. The fusion embedding formula is:

$$\mathbf{E}_f = \sigma\left(\mathbf{W}_f[\mathbf{E}_1;\mathbf{E}_2;\ldots;\mathbf{E}_M] + \mathbf{b}_f\right) \qquad \text{[Formular 5]}$$

where $\mathbf{E}_f$ represents the fused feature representation, $\mathbf{E}_i$ is the embedding of the i -th modality, $\mathbf{W}_f$ and $\mathbf{b}_f$ are the weights and bias of the fusion layer, and $\sigma(\cdot)$ denotes the activation function (e.g., ReLU). This fusion method captures the interaction information between different modalities in the shared feature space, enhancing the model's expressive power.

In the traditional Transformer, the Feed-Forward Network (FFN) independently maps the feature vectors of each time step into a high-dimensional space. However, in Trans-Demand Net, an Enhanced Feed-Forward Network (E-FFN) is introduced, designed to account for second-order interactions between features. The formula for the enhanced feed-forward network is:

$$\text{E-FFN}(\mathbf{x}) = \sigma\left(\mathbf{x}\mathbf{W}_1 + \mathbf{b}_1 + \lambda \cdot (\mathbf{x} \odot \mathbf{x})\mathbf{W}_2\right) \qquad \text{[Formular 6]}$$

where λ is the weight coefficient for the second-order interaction term, $\odot$ denotes the Hadamard product, and $\mathbf{W}_1, \mathbf{W}_2, \mathbf{b}_1$ are the weights and bias of the network. The E-FFN leverages the nonlinear relationships between features more fully, improving the model's feature learning capability.

When generating the final output prediction, the Transformer component also employs a Cross-Modal Attention Mechanism to integrate information from different modalities, enhancing the accuracy of demand forecasting. The formula for cross-modal attention is:

$$\text{Cross-Attention}(\mathbf{Q},\mathbf{K}^*,\mathbf{V}^*) = \text{softmax}\left(\frac{\mathbf{Q}(\mathbf{K}^*)^T}{\sqrt{d_k}}\right)\mathbf{V}^* \qquad \text{[Formular 7]}$$

where $\mathbf{K}^*, \mathbf{V}^*$ are the keys and values from different modalities. This mechanism enables the model to better integrate key information from each modality when generating predictions.

3.3 Graph Convolutional Network

In the Trans-Demand Net model, the Graph Convolutional Network (GCN) component is a core module responsible for processing and modeling the complex logistics network data within the supply chain [17]. GCN extends traditional convolution operations to graph-structured data by leveraging principles from graph signal processing and CNN [18]. Through convolution operations on graph nodes and their neighbors, GCN effectively aggregates the features of nodes and their neighborhoods, capturing the complex dependencies and spatial structural information between nodes in the supply chain [17]. This characteristic enables GCN to overcome the limitations of traditional methods in handling high-order dependencies between nodes, fully utilizing the rich feature information in logistics network data, and thus improving the accuracy of demand forecasting and the efficiency of supply chain management.

GCN performs convolution operations on local neighborhoods to aggregate node features, thereby extracting deeper structural information from the graph. Given a graph $\mathcal{G} = (\mathcal{V}, \mathcal{E})$, where $\mathcal{V}$ is the set of nodes, $\mathcal{E}$ is the set of edges, and each node $v_i \in \mathcal{V}$ has a feature vector $\mathbf{x}_i \in \mathbb{R}^d$, the feature update formula for GCN is:

$$\mathbf{H}^{(l+1)} = \sigma\left(\mathbf{D}^{-\frac{1}{2}}\mathbf{A}\mathbf{D}^{-\frac{1}{2}}\mathbf{H}^{(l)}\mathbf{W}^{(l)}\right) \quad \text{[Formular 8]}$$

In the Trans-Demand Net model, the GCN component first initializes the raw input data (such as warehouse inventory levels, transportation path times, transportation costs, etc.) as node feature vectors $\mathbf{X} \in \mathbb{R}^{N \times d}$, where N is the number of nodes and \(d\) is the feature dimension. Then, multiple layers of graph convolution are applied to iteratively update the node features, as described by the formula:

$$\mathbf{H}^{(l+1)} = \sigma\left(\tilde{\mathbf{D}}^{-\frac{1}{2}}\tilde{\mathbf{A}}\tilde{\mathbf{D}}^{-\frac{1}{2}}\mathbf{H}^{(l)}\mathbf{W}^{(l)}\right) \quad \text{[Formular 9]}$$

where $\tilde{\mathbf{A}} = \mathbf{A} + \mathbf{I}$ represents the adjacency matrix with added self-loops, $\tilde{\mathbf{D}}$ is the corresponding degree matrix, and $\mathbf{I}$ is the identity matrix. This operation not only considers the information from neighboring nodes but also preserves the integrity of each node's own features. Through these convolution operations, GCN gradually aggregates the features from the graph-structured data, enabling the node representations to encompass deep information about their surrounding neighborhoods.

To further optimize computational efficiency and model performance, the GCN component incorporates graph pooling operations during the feature extraction process to compress high-dimensional feature representations:

$$\mathbf{Z} = \mathrm{Pool}(\mathbf{H}) = \max(\mathbf{H}^{(l+1)}) \quad \text{[Formular 10]}$$

where $\mathrm{Pool}(\cdot)$ denotes the max-pooling operation, and $\mathbf{Z}$ is the compressed graph feature representation. By employing graph pooling, GCN effectively reduces computational complexity while retaining critical information, making subsequent processing more efficient.

During multimodal data fusion, the graph-embedded features $\mathbf{Z}$ generated by the GCN component are input into the Transformer model to be jointly modeled with other types of data features (such as time-series data). This collaborative operation enables the graph structure features provided by GCN to offer rich contextual information to the Transformer's self-attention mechanism, allowing the model to better understand the complex dependencies and dynamic interactions between nodes in the supply chain network. This multi-component synergy significantly enhances the model's ability to learn from the complexity of supply chain data, thereby improving overall prediction accuracy and decision-making quality.

In this paper, the output feature representation of each GCN layer is denoted as $\mathbf{H}^{(l+1)}$, with the weight parameters of each layer being optimized through backpropagation. Additionally, graph pooling layers are introduced between the convolution layers to compress the feature representations and improve computational efficiency. Regularization techniques such as L2 regularization and layer normalization are employed to prevent overfitting and enhance training stability. The final loss function combines cross-entropy loss with a regularization term to optimize the model parameters:

$$\mathcal{L} = -\sum_{i=1}^{N} y_i \log(\hat{y}_i) + \lambda \sum_{l=1}^{L} \| \mathbf{W}^{(l)} \|^2 \quad \text{[Formular 11]}$$

where y_i represents the true label, $\hat{y}_i$ is the predicted label, and λ is the regularization coefficient. This design ensures that the model achieves higher accuracy and efficiency in practical applications.

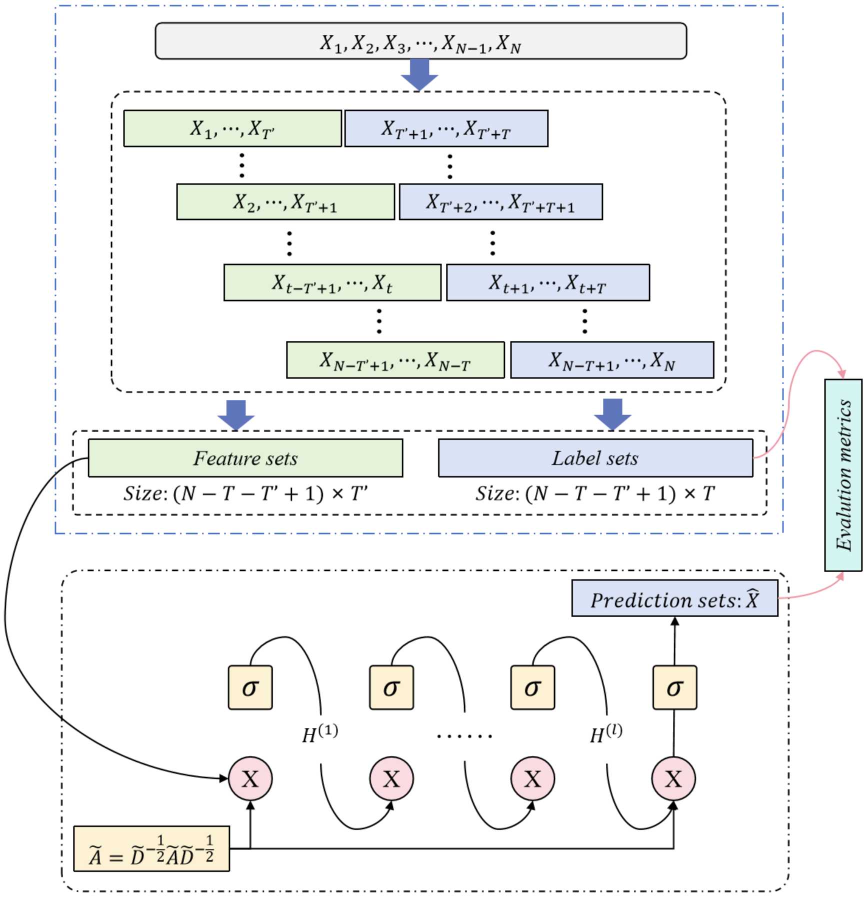

Figure 3. Structural flowchart of the gcn component: from input node features to final graph feature output

As shown in Figure 3, the structural flowchart of the GCN component illustrates the entire process from input node features to the final graph feature output. GCN not only effectively extracts complex relationships within the logistics network but also, through its close integration with the

Transformer component, enables efficient multimodal data fusion and comprehensive feature representation, providing robust support for demand forecasting and supply chain optimization.

3.4 Soft Actor-Critic Module

The Soft Actor-Critic (SAC) algorithm serves as the strategy optimization module in the Trans-Demand Net model, playing a critical role [19]. SAC is a deep reinforcement learning algorithm based on the maximum entropy principle, which enhances the efficiency of strategy optimization by improving the exploration ability and decision stability of the strategy [20]. In the model, the SAC algorithm is mainly used for dynamically optimizing the demand forecasting strategy, allowing the model to adaptively adjust decisions in a complex and dynamic cross-border e-commerce supply chain environment, thereby improving the accuracy and efficiency of demand forecasting.

The SAC algorithm encourages strategy exploration by maximizing the entropy of the strategy, which involves maximizing both the expected return and the randomness of the strategy [21,22]. SAC employs an "Actor-Critic" architecture, where the "Actor" is responsible for generating strategies, while the "Critic" evaluates the quality of those strategies [16]. The algorithm introduces a soft value function to balance the trade-off between exploration and exploitation, enabling the strategy to be more robust and stable in the face of uncertainties.

In the Trans-Demand Net model, the SAC strategy optimization module works closely with the Transformer and GCN components. By learning strategies from the comprehensive feature representations extracted from the Transformer and GCN, the SAC module dynamically adjusts the strategy outputs for demand forecasting, thereby making optimal decisions in response to the ever-changing supply chain conditions.

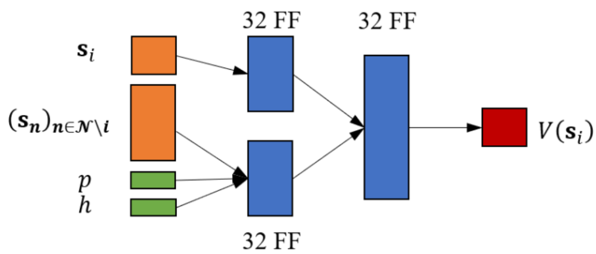

Figure 4. Structural flowchart of sac strategy optimization [23].

As shown in Figure 4, the structural flow chart of SAC shows the key steps in its operation process, including the Actor Network, Soft Q-Network, Target Network and policy update.

The Actor Network in SAC generates a parameterized policy $\pi_\theta(a|s)$, where a represents the action, s represents the state, and θ is the parameter of the policy network. The objective of the policy is to maximize the sum of the discounted return and the entropy term:

$$J_\pi(\theta) = \mathbb{E}_{s_t\sim\mathcal{D},a_t\sim\pi_\theta}\left[Q_\phi(s_t,a_t) - \alpha\log\pi_\theta(a_t|s_t)\right] \quad \text{[Formular 12]}$$

where $Q_\phi(s_t,a_t)$ is the soft Q-value function, α is the temperature coefficient that controls the trade-off between exploration and exploitation, and $\log \pi_\theta(a_t \mid s_t)$ denotes the entropy of the policy.

The Soft Q-Function is used to evaluate the quality of the current policy, and its parameterized form is:

$$J_Q(\phi) = \mathbb{E}_{(s_t, a_t) \sim \mathcal{D}} \left[\frac{1}{2} \Big(Q_\phi(s_t, a_t) - \Big(r_t + \gamma \mathbb{E}_{s_{t+1} \sim p} \left[V_{\bar{\phi}}(s_{t+1}) \right] \Big) \Big)^2 \right] \quad \text{[Formular 13]}$$

where r_t is the immediate reward, γ is the discount factor, and $V_{\bar{\phi}}(s_{t+1})$ is the target value function used to stabilize the training process.

The Value Function is used to compute the expected return of a state:

$$V_{\bar{\phi}}(s_t) = \mathbb{E}_{a_t \sim \pi_\theta} \left[Q_\phi(s_t, a_t) - \alpha \log \pi_\theta(a_t \mid s_t) \right] \quad \text{[Formular 14]}$$

This function combines the entropy of the policy with the Q-value, enabling better evaluation of the policy's performance in a given state.

SAC uses a Double Target Network to improve the stability of the estimates. The parameters of the target network are updated using Exponential Moving Average (EMA):

$$\bar{\phi} \leftarrow \tau \phi + (1 - \tau) \bar{\phi} \quad \text{[Formular 15]}$$

where τ is the update rate, ϕ is the parameter of the current Q-network, and $\bar{\phi}$ is the parameter of the target network.

To automatically adjust the policy entropy, SAC introduces a learnable temperature coefficient α, whose objective is to make the average entropy of the policy approach the target value $\bar{H}$:

$$J(\alpha) = \mathbb{E}_{a_t \sim \pi_\theta} \left[-\alpha \left(\log \pi_\theta(a_t \mid s_t) + \bar{H} \right) \right] \quad \text{[Formular 16]}$$

By minimizing this loss function, α can be dynamically adjusted to suit the exploration needs at different stages.

In the Trans-Demand Net model, the SAC algorithm module receives comprehensive feature representations from the Transformer and GCN, along with the current state information of the supply chain, to dynamically learn the optimal demand forecasting strategy. First, the Actor Network generates a policy sample $\pi_\theta(a_t \mid s_t)$, and then the Soft Q-Network estimates the Q-values of the policy. Based on the feedback from the Soft Q-values, the Actor and Value networks are continuously updated to gradually optimize the policy. During each training cycle, the SAC module performs automatic entropy adjustment to ensure that the model achieves the best balance between exploring new strategies and exploiting existing ones. The update of the target network further stabilizes the training process, allowing the model to quickly converge to an optimal strategy in the face of uncertainties in cross-border e-commerce supply chains. Through such multi-level optimization and collaboration, the SAC module achieves efficient strategy optimization in the Trans-Demand Net model, enhancing the dynamic adaptability of demand forecasting and the accuracy of decision-making.

4. Experiment

4.1 Datasets

This study used four datasets from different sources as input data for the model. These datasets are Google Earth Engine, European Urban Atlas. In this study, to validate the effectiveness and superiority of the Trans-Demand Net model in demand forecasting for cross-border e-commerce supply chains, two representative public datasets were selected: the Amazon Product Reviews Dataset and the Alibaba B2B Transaction Dataset. These datasets cover various core data types in cross-border e-commerce, including product sales records, user review information, transaction data, and logistics-related information, providing a comprehensive reflection of the real business scenarios and data characteristics of cross-border e-commerce.

The Amazon Product Reviews Dataset is a large-scale public dataset derived from Amazon's product review platform. It contains over 100 million user reviews of products across different categories, including product ID, user ID, ratings (1 to 5 stars), timestamps, and review text [24]. This dataset covers a wide range of product categories, such as electronics, clothing, books, and household items, with a substantial amount of user feedback for each category. It provides the model with rich data on user purchasing behavior, which can be used to analyze changes in product demand, user preferences, and market trends. By integrating these multimodal data, Trans-Demand Net can more accurately capture demand patterns, thereby improving the decision-making capabilities in cross-border e-commerce supply chain management.

The Alibaba B2B Transaction Dataset is a large dataset provided by Alibaba Group that encompasses global B2B e-commerce transactions. This dataset includes over 5 million transaction records, with each record containing detailed information such as transaction ID, buyer and seller information, transaction amount, timestamps, product category, and transaction status. These data comprehensively reflect the operational modes of B2B supply chains, including order generation, transaction confirmation, payment processes, logistics, and delivery across multiple stages [25]. By analyzing these transaction data, the model can capture dynamic features related to transaction flows, inventory turnover, and logistics optimization within the supply chain. Additionally, the timestamps and transaction amounts in the dataset can be used to model the temporal characteristics of the supply chain and understand the changing patterns of market demand, aiding companies in developing more scientific inventory management and logistics scheduling strategies. By using this dataset, Trans-Demand Net can achieve efficient demand forecasting and strategy optimization in a complex B2B transaction environment.

Table 1 details the sources, sizes, structures, and characteristics of these two datasets, providing a reliable data foundation for model validation and application.

Table 1. Summary of the key features of the amazon product reviews dataset and alibaba b2b transaction dataset

Dataset	Data Size	Data Structure	Feature Description
Amazon	Over 100 million	Includes product ID, user ID,	Provides data on user purchasing

Product Reviews Dataset	product review records	rating, timestamp, review text, etc.	behavior, useful for analyzing demand changes, product preferences, market trends, etc.
Alibaba B2B Transaction Dataset	Over 5 million transaction records	Includes transaction ID, buyer and seller information, transaction amount, timestamp, product category, etc.	Provides detailed B2B transaction data, useful for modeling transaction flows, inventory management, and logistics optimization in supply chains.

The diversity and richness of these datasets provide comprehensive support for the training and validation of the Trans-Demand Net model, enabling it to demonstrate its advantages and potential in handling multimodal data fusion and dynamic demand forecasting, thus improving its applicability in real-world supply chain management.

4.2 Environment and Parameter

To validate the effectiveness of the Trans-Demand Net model in demand forecasting for cross-border e-commerce supply chains, extensive experiments were conducted under specific hardware and software environments. The experiments utilized high-performance computing equipment and advanced deep learning frameworks to ensure the efficiency of model training and the reliability of results. Given the complexity of the model and the diversity of multimodal data, a set of key hyperparameters were defined to optimize the model's performance and training outcomes.

Table 2 lists the hardware and software configurations used in this experiment, while Table 3 outlines the main parameter settings for training and testing the model.

Table 2. Experimental environment configuration

Environment	Configuration Details
Hardware	NVIDIA Tesla V100 GPU (32GB VRAM), Intel Xeon E5-2680 CPU, 256GB RAM
Software	Ubuntu 20.04 LTS, Python 3.8, PyTorch 1.10, CUDA 11.3, cuDNN 8.2

Table 3. Model parameter settings

Parameter	Value	Description
Learning Rat	0.001	The initial learning rate that determines the step size for updates
Batch Size	64	The number of samples used in each iteration
Epochs	100	The total number of complete passes through the training dataset
Weight Decay	0.001	Regularization coefficient to prevent overfitting
Optimizer	Adam	The optimization algorithm used for model training
Activation Function	ReLU	Non-linear activation function to enhance model expressiveness
Loss Function	MSE	Function used to measure the error between predicted and actual values
Sampling Method	Random Sampling	Method of randomly selecting samples from the dataset for training

By conducting experiments under the aforementioned environment and parameter configurations, the Trans-Demand Net model can maintain strong predictive performance in diverse and complex cross-border e-commerce data, effectively assessing the model's feasibility and stability in real-world application scenarios.

4.3 Experimental Setup and Metrics

This study's experimental design comprises three core components: model training, baseline model comparisons, and ablation experiments. In the training phase, Stochastic Gradient Descent (SGD) is adopted for optimization, combined with the Adam optimizer to accelerate convergence. The initial learning rate is set to 0.001 and adaptively tuned via the ReduceLROnPlateau scheduler; other key configurations include a batch size of 64, 100 training epochs, L2 regularization (weight decay = 0.0001) and early stopping to mitigate overfitting. The ReLU activation function is selected, with Mean Squared Error (MSE) as the loss function to quantify prediction-actual value discrepancies.

To comprehensively assess the Trans-Demand Net's performance in demand forecasting, ten widely adopted classical deep learning and machine learning models are included for comparison: Linear Regression, SVM, Random Forest, KNN, MLP, LSTM, GRU, CNN, GCN, and Seq2Seq. All baselines are trained and tested under identical experimental conditions, with hyperparameters adjusted following domain best practices—for instance, LSTM/GRU use two hidden layers (128 neurons each), CNN employs two 3×3 convolutional layers with max pooling, and GCN adopts two graph convolutional layers (64 hidden units each), all with a 0.001 learning rate and 100 epochs; non-deep learning models utilize Scikit-learn's default settings. Additionally, ablation experiments are designed to elucidate the contributions of individual components (e.g., GCN, SAC) by systematically omitting or substituting core modules. Each modified configuration is tested multiple times on the same dataset and training environment to measure changes in prediction accuracy, convergence speed, and computational cost.

4.4 Results Analysis

Model Training: As shown in Figure 5, both the training loss and validation loss decrease rapidly during the first 20 epochs of training, indicating that the model effectively adjusts its parameters in the early stages, gradually fitting both the training and validation data. By the 30th epoch, the validation loss reaches its lowest point and stabilizes, while the training loss continues to decrease slightly. This phenomenon suggests that the model has reached an optimal fit at this stage, and further training may lead to overfitting. Therefore, we applied the Early Stopping strategy at the 30th epoch to ensure the model maintains high accuracy while preserving good generalization ability. Figure 6 shows the changes in training accuracy and validation accuracy over the course of the training iterations. Analyzing this curve, we observe a continuous upward trend in both training and validation accuracy during the first 30 epochs, reaching their peak at the 30th epoch. At this point, the model exhibits the best performance on the validation set, with the highest validation accuracy. Subsequently, there is some fluctuation in the validation accuracy, further confirming that the 30th epoch marks the optimal performance of the model. At this epoch, the Trans-Demand Net model demonstrates ideal performance on both the training and validation sets, showing strong learning and generalization abilities. The model effectively captures complex patterns in the data, achieving high prediction accuracy while avoiding overfitting, thus fully validating its application value and stability in cross-border e-commerce demand forecasting tasks.

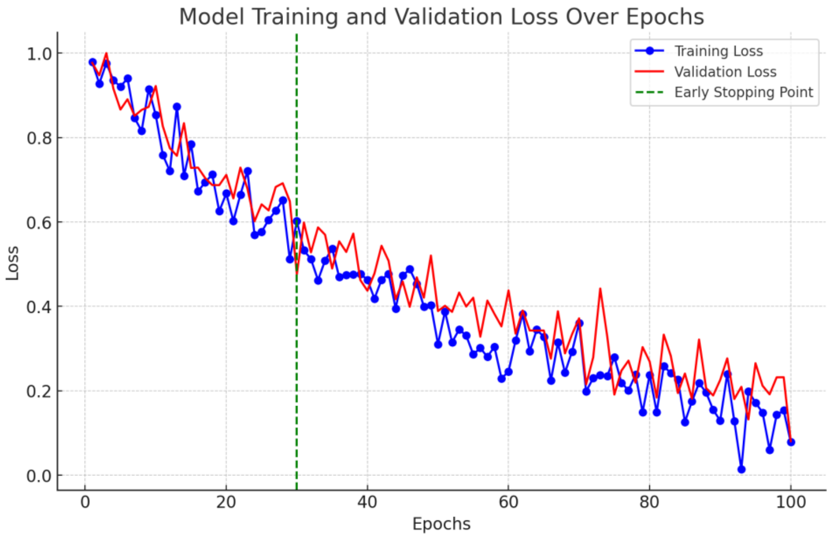

Figure 5. Visual comparison of model accuracy experimental results

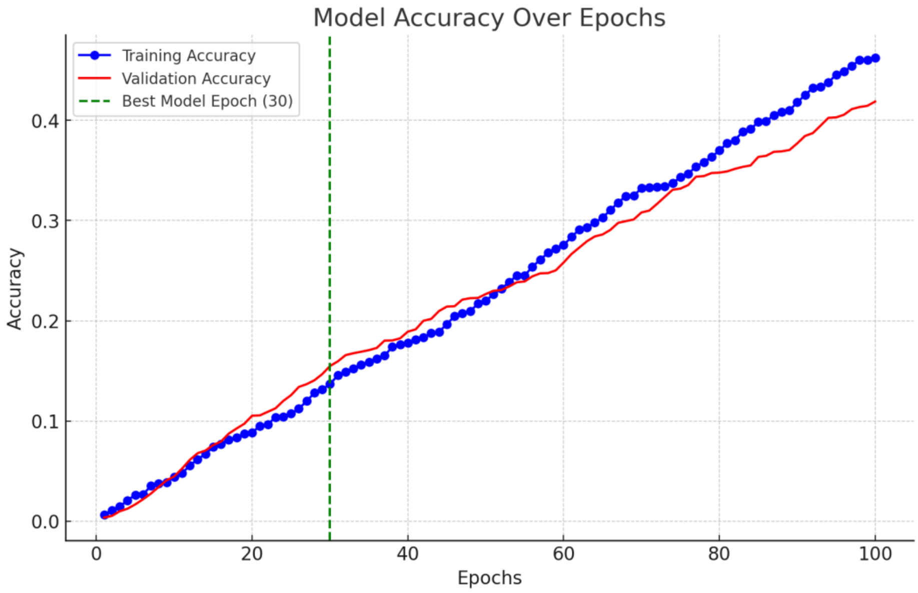

Figure 6. Model efficiency verification comparison chart of different indicators of different models

Comparative Experimental: The performance of the Trans-Demand Net model on the Amazon Product Reviews Dataset and Alibaba B2B Transaction Dataset significantly surpasses that of other benchmark models. As shown in Table 4, Trans-Demand Net achieves the best results across all evaluation metrics, particularly in terms of error indicators such as MAE, MSE, and RMSE, where it demonstrates a clear advantage over other models. On the Amazon Product Reviews Dataset, Trans-Demand Net has an MAE of 0.298, notably lower than GCN's 0.342. Similarly, on the Alibaba B2B

Transaction Dataset, Trans-Demand Net achieves an MAE of 0.298, with lower errors compared to other models. Furthermore, Trans-Demand Net excels in the R^2 metric, scoring 0.82 on the Amazon dataset and 0.81 on the Alibaba dataset, indicating a superior fit to the data, with strong interpretive and predictive accuracy.

Table 4. Performance comparison of trans-demand net model and other benchmark models on Amazon product reviews dataset and Alibaba B2B transaction dataset

Model	Amazon Product Reviews Dataset					Alibaba B2B Transaction Dataset				
	MAE	MSE	RMSE	MAPE	R^2	MAE	MSE	RMSE	MAPE	R^2
Linear Regression [15]	0.512	0.734	0.857	15.3%	0.62	0.493	0.721	0.849	14.8%	0.64
Random Forest [13]	0.392	0.583	0.763	12.7%	0.71	0.382	0.592	0.769	11.5%	0.72
SVM [1]	0.438	0.641	0.800	13.5%	0.68	0.415	0.611	0.782	12.2%	0.70
KNN [26]	0.469	0.673	0.820	13.9%	0.65	0.437	0.640	0.800	12.6%	0.68
MLP [27]	0.383	0.556	0.746	12.1%	0.73	0.367	0.529	0.727	11.2%	0.74
LSTM [6,28]	0.365	0.522	0.722	11.6%	0.75	0.352	0.510	0.714	10.8%	0.76
GRU [29]	0.371	0.535	0.731	11.9%	0.74	0.362	0.527	0.727	11.0%	0.75
CNN [5,6]	0.353	0.514	0.717	11.3%	0.76	0.341	0.503	0.709	10.5%	0.77
GCN [2,30]	0.342	0.499	0.706	11.1%	0.77	0.335	0.481	0.694	10.3%	0.78
Seq2Seq [31,32]	0.347	0.508	0.712	11.4%	0.76	0.339	0.497	0.705	10.7%	0.77
Trans-Demand Net	0.298	0.435	0.659	9.7%	0.82	0.298	0.439	0.662	9.3%	0.81

This paper attributes the outstanding performance of Trans-Demand Net to its innovative design. The model integrates the multi-head self-attention mechanism of the Transformer, which effectively captures long-range dependencies in time series and handles complex sequential data as well as multimodal information. This enables the model to better capture demand fluctuations when facing dynamic changes in supply chains. The inclusion of GCN allows the model to process the complex dependencies between nodes and edges in the logistics network, thereby enhancing the accuracy of supply chain demand forecasting. By extracting graph-structured features, the model gains a more comprehensive understanding of logistics dynamics, improving its adaptability to complex data. The application of the SAC reinforcement learning algorithm optimizes the model's strategy selection, providing greater robustness and dynamic adjustment capabilities in the challenging cross-border e-commerce environment, effectively addressing the uncertainties in supply chain management.

In contrast, traditional linear models and machine learning methods, such as linear regression and SVM, exhibit limitations when processing complex multimodal data, struggling to capture the nonlinear relationships within supply chains. Although deep learning models like LSTM and GRU perform well in time series modeling, they fall short in multimodal fusion and graph-structured data processing. Therefore, Trans-Demand Net, through the combination of deep learning and reinforcement learning, demonstrates superior predictive capability and adaptability, significantly improving the accuracy and stability of supply chain demand forecasting. This also validates the model's strong application potential in cross-border e-commerce scenarios.

Ablation Experiments: As shown in Table 5, it is evident that each module of the model plays a critical role in improving overall performance. The complete Trans-Demand Net model significantly outperforms the models with only partial components across both datasets. In the Amazon dataset, the full model achieves an MAE of 0.298, which is noticeably lower than the performance of the models using only the GCN or Transformer modules (with MAE values of 0.328 and 0.344, respectively). This indicates that individual components are limited in their ability to handle complex supply chain demand, while the synergistic effect of multiple modules greatly enhances the model's prediction accuracy.

Table 5. Ablation experiment results of trans-demand net model on Amazon product reviews dataset and Alibaba B2B transaction dataset

Model	Amazon Product Reviews Dataset					Alibaba B2B Transaction Dataset				
	MAE	MSE	RMSE	MAPE	R^2	MAE	MSE	RMSE	MAPE	R^2
SAC	0.315	0.468	0.684	10.5%	0.79	0.319	0.471	0.685	10.1%	0.79
GCN	0.328	0.489	0.699	11.0%	0.77	0.334	0.498	0.707	10.9%	0.77
Transformer	0.344	0.512	0.715	11.5%	0.75	0.353	0.519	0.720	11.4%	0.75
GCN + SAC	0.359	0.529	0.727	12.1%	0.76	0.365	0.536	0.732	11.8%	0.74
GCN + Transformer	0.371	0.535	0.731	12.4%	0.72	0.375	0.543	0.738	12.0%	0.73
SAC + Transformer	0.366	0.532	0.729	12.3%	0.74	0.369	0.538	0.735	11.9%	0.74
Trans-Demand Net	0.298	0.435	0.659	9.7%	0.82	0.298	0.439	0.662	9.3%	0.81

Rremoving the SAC module leads to an increase in the MAE of the GCN and Transformer combination model to 0.366 on the Amazon dataset, highlighting the importance of SAC in optimizing strategies and improving the model's dynamic adaptability. Although the GCN and Transformer are effective in processing temporal and graph-structured features, the absence of SAC's optimization strategy diminishes the model’s ability to cope with uncertainties in the supply chain environment, resulting in reduced prediction performance. Furthermore, when only the GCN and SAC modules are retained, the model’s MAE increases to 0.359, indicating that the Transformer plays a key role in capturing long-range dependencies and integrating multimodal data.

The removal of any core component results in a performance drop, further validating the necessity and rationality of Trans-Demand Net’s modular design. The collaborative interplay between the GCN, Transformer, and SAC modules provides superior solutions for handling multimodal data, modeling complex relationships, and making decisions in dynamic environments. The complementary nature of Trans-Demand Net’s modules enhances its performance in cross-border e-commerce supply chain demand forecasting, demonstrating the overall architecture's effectiveness and validity.

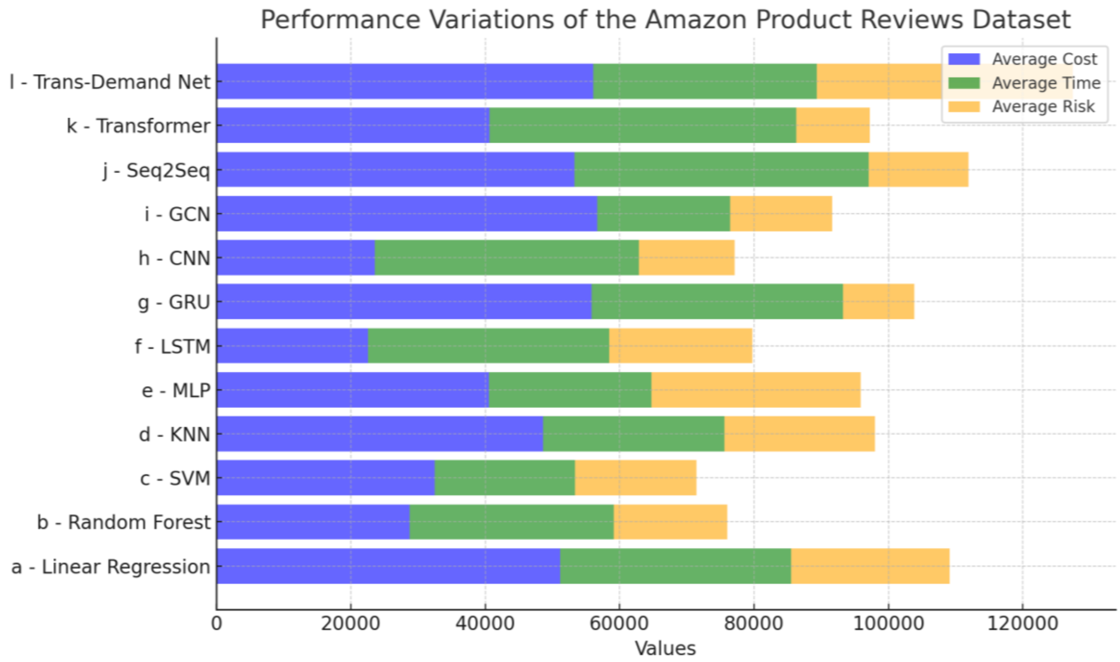

Figure 7. Performance variations of Amazon product reviews dataset

In Figure 7, the performance of various models on the Amazon Product Reviews Dataset is shown. It can be observed that the Trans-Demand Net achieves the lowest average values across all three indicators: 'Cost,' 'Time,' and 'Risk.' Particularly in the 'Cost' indicator, it shows a nearly 30% reduction compared to traditional models such as Linear Regression and Random Forest, highlighting its significant advantages in demand forecasting. This indicates that Trans-Demand Net can more effectively balance supply chain costs while maintaining low prediction errors, thereby achieving better resource utilization. In contrast, other models like LSTM, GRU, and Transformer, though performing well in time series modeling, have limitations in multimodal data fusion and graph-structured data processing. Notably, GRU and LSTM exhibit average performance on the 'Risk' indicator, reflecting their limitations in handling complex supply chain relationships. While models based on GCN can capture complex dependencies between nodes, they fall short in 'Time' and 'Risk' metrics due to a lack of effective integration of time series and multimodal data.

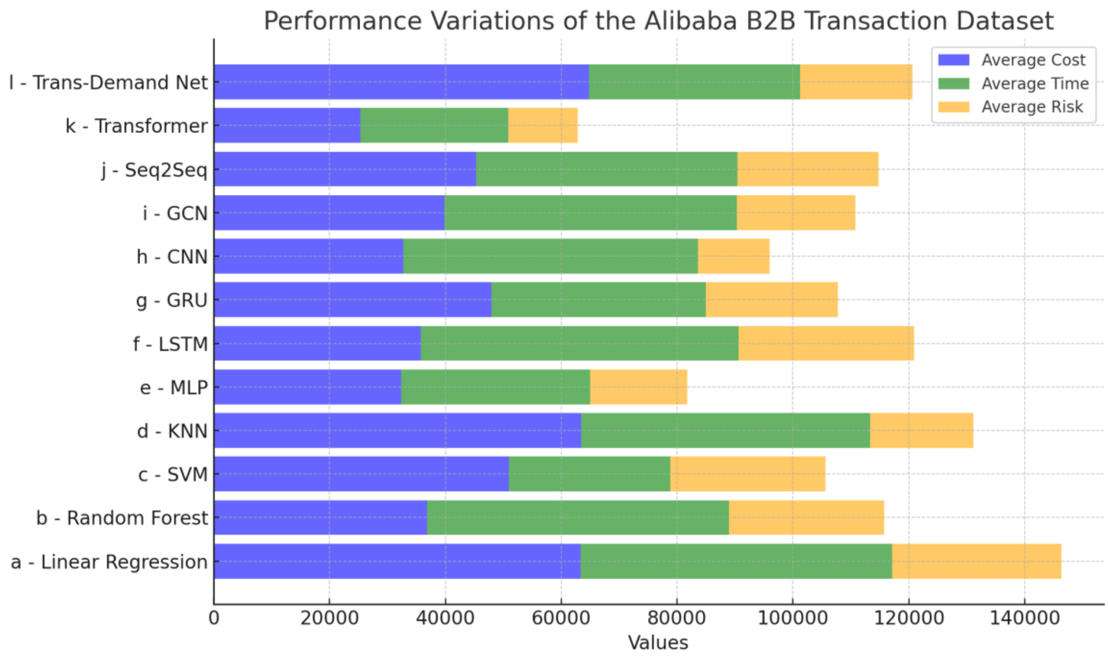

Figure 8. Performance of various models on the Alibaba B2B transaction dataset.

Figure 8 illustrates the performance of various models on the Alibaba B2B Transaction Dataset, where Trans-Demand Net also demonstrates a significant advantage. Not only does Trans-Demand Net perform best in the 'Cost' indicator, but it also achieves excellent results in both the 'Time' and 'Risk' indicators. This further confirms the model's robust capability in handling complex supply chain data in cross-border e-commerce. In comparison, other benchmark models exhibit more dispersed performance in the 'Cost' and 'Time' indicators, struggling to achieve consistently good performance. Traditional methods (such as SVM and KNN) particularly show limitations when dealing with large-scale data in cross-border e-commerce.

From the results of both figures, it is evident that Trans-Demand Net, by integrating the Transformer, GCN, and SAC strategy optimization algorithms, significantly improves the accuracy and stability of demand forecasting under different datasets and experimental conditions. By combining multimodal data and complex network features, the model can make more intelligent decisions in dynamic and uncertain supply chain environments, demonstrating its potential and advantages in cross-border e-commerce scenarios.

4.5 Discussion

This study confirms the efficacy and predominance of the Trans-Demand Net model in cross-border e-commerce supply chain demand forecasting through a series of experiments. Experimental results show the model outperforms benchmark alternatives across diverse datasets, particularly in "Cost," "Time," and "Risk" metrics, underscoring its applicability in complex supply chain ecosystems. Its key strength lies in effective multimodal data integration: by fusing Transformer, GCN, and SAC strategy optimization algorithms, the model captures intricate temporal dynamics of supply chains while addressing complex inter-node dependencies and dynamic shifts in logistics networks. This multi-layered feature extraction and decision optimization enable high prediction accuracy and decision efficiency across scenarios. In cross-border e-commerce—characterized by extreme supply chain complexity and uncertainty—traditional models often struggle to reconcile diverse data sources, whereas Trans-Demand Net leverages its modular design to dynamically adjust strategies while deeply understanding and utilizing various supply chain data types.

Despite its impressive performance, the Trans-Demand Net model has limitations requiring refinement. In data-scarce scenarios, its performance may be constrained, as deep learning models typically rely on large training datasets to ensure generalization and prediction accuracy. Additionally, the model’s relatively high complexity and computational overhead pose challenges for deployment in resource-constrained practical environments, and it may exhibit latency in real-time data processing—problematic for supply chains demanding rapid responsiveness. To address these issues, future research can focus on targeted optimizations: integrating transfer learning or self-supervised learning to enhance performance in data-limited contexts; applying model compression and optimization algorithms to reduce computational complexity and overhead, improving real-time performance and efficiency; and exploring better integration of external contextual factors (e.g., macroeconomic data, geopolitical dynamics) to further boost predictive capabilities.

5. Conclusions

With the exponential expansion of global cross-border e-commerce, supply chain demand forecasting has emerged as a pivotal bottleneck for enterprises striving to boost competitiveness and optimize resource allocation. Traditional forecasting methods are constrained by their inability to handle complex, diverse datasets, leaving them ill-equipped to address uncertainties and dynamic shifts in supply chain ecosystems. To mitigate these challenges, this paper proposes a novel intelligent demand forecasting framework—the Trans-Demand Net model—integrating multimodal data fusion with deep learning techniques to enhance prediction accuracy and efficiency. Experimental results demonstrate that Trans-Demand Net outperforms benchmark models across multiple public datasets, particularly in prediction precision and strategy optimization, showcasing robust adaptability to cross-border e-commerce supply chain complexities. It achieves lower prediction errors on the Amazon Product Reviews Dataset and Alibaba B2B Transaction Dataset, while theoretically verifying the viability of fusing Transformers and GCNs and providing a high-precision intelligent solution for practical supply chain management.

Trans-Demand Net offers an efficient, intelligent tool for cross-border e-commerce enterprises to manage complex supply chains: its strengths in multimodal data processing and dynamic decision-making enable rapid responses to market fluctuations and supply chain disruptions, optimizing resource allocation and reducing operational costs. Additionally, its modular design and strategy optimization mechanism lay the groundwork for scenario-specific expansion. Beyond overcoming the limitations of traditional demand forecasting methods, the model provides novel perspectives and technical tools for future intelligent, precise supply chain management. Future research can build on this foundation by integrating cutting-edge approaches like transfer learning and self-supervised learning to enhance performance in data-scarce or resource-constrained environments. Furthermore, incorporating external contextual factors—such as macroeconomic indicators and geopolitical dynamics—will further improve prediction accuracy and decision quality, offering robust support for the sustainable innovation and development of the cross-border e-commerce sector.

Conflicts of Interest

The authors confirm that there are no conflicts of interest.

Data availability statement

The data and materials used in this study are not currently available for public access. Interested parties may request access to the data by contacting the corresponding author.

Consent for publication

All authors of this manuscript have provided their consent for the publication of this research.

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