Dynamic Tangent Search-Driven Graph Neural Networks for Cross-Border E-Commerce Sales Forecasting

Sicong Li
School of Economics and Management, Shaoyang University, Shaoyang, Hunan 422000, China
E-mail: sicong331li@hotmail.com

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The rapid expansion of cross-border e-commerce has intensified the need for accurate and computationally efficient sales forecasting models capable of capturing complex user–product interactions and dynamic market behavior. Traditional machine learning (ML) approaches often fail to model multi-hop relational dependencies and volatile browsing patterns across international platforms. To address these challenges, this study proposes a Dynamic Tangent Search–driven Graph Neural Network (DTS-GNN) framework for cross-border e-commerce sales forecasting. The proposed methodology integrates comprehensive data preprocessing, including noise removal, missing value imputation, Min–Max normalization, and one-hot encoding, followed by Principal Component Analysis (PCA) for dimensionality reduction and feature extraction. A Graph Neural Network (GNN) is employed to model relational structures among users and products, while Dynamic Tangent Search (DTS) is used to adaptively optimize graph weights and hyperparameters, improving convergence stability and prediction accuracy. The model is evaluated using a real-world cross-border e-commerce dataset comprising 2,100 records of user browsing behavior, product attributes, and transactional data. Experimental results demonstrate that the proposed DTS-GNN significantly outperforms existing models, achieving a Mean Absolute Error (MAE) of 1.8420, Root Mean Square Error (RMSE) of 2.2165, Normalized RMSE of 0.0568, Mean Absolute Percentage Error (MAPE) of 10.3924, and a correlation coefficient (R) of 0.9448. Additionally, the framework shows improved reliability (24.6), reduced uncertainty (17.3), and faster search time (10.9 s). These results confirm the effectiveness, robustness, and computational efficiency of the DTS-GNN framework for accurate sales forecasting in dynamic cross-border e-commerce environments.

Povzetek: Predlagan model DTS-GNN za napoved prodaje v čezmejni e-trgovini izboljša natančnost, stabilnost in učinkovitost z uporabo grafnih nevronskih mrež in optimizacije DTS ter presega obstoječe metode.

1 Introduction

In the modern world, knowledge plays an indispensable role in the long-term, healthy growth of companies and is progressively becoming a significant force for businesses to enhance the core competitiveness of individuals and consistently acquire competitive advantages [1]. In an e-commerce firm, the seller must be unable to escape the issue of order replenishment, regardless of the size of their store. The two primary issues with order replenishment are the cash flow issue and the inventory issue [2]. As living standards rise and electronic networks become more and more ingrained in daily life, cross-border e-commerce is beginning to take center stage in the retail industry. The expansion of global internet commerce has sped up the growth of the logistics sector. A problem in the continuous flow of cold-chain products in international e-commerce has been noticed [3]. Obtaining a comprehensive sample of the data has become easy because of the Internet, intensive data technology, e-commerce, and the development of mobile phones. This is due to the ease of acquiring consumer-generated and consumer-retained data while making remote purchases. In this way, through an assessment of the generated consumer data, the online business enterprises can identify the preference of various consumer groups for different products, thus identifying the potential of each type of product in various time spans [4]. A new idea of cross-border live-streaming e-commerce has emerged because of the current acceleration of broadcasting technology due to the growth of short video platforms. In international e-commerce, live streaming has grown in importance as a sales medium. Real-time presentation and immersive shopping experiences have significantly raised customer conversion rates [5, 6]. Any kind of commercial transaction carried out online is referred to as e-commerce. E-commerce involves buying, mixing, businesses, government, or consumer entities depending on the type of transaction itself [7]. Figure 1 depicts a thorough cross-border e-commerce pipeline that incorporates foreign platforms, sellers, apps, and delivery firms. While docking platforms enable communication, they depict administrators overseeing content, finance, delivery, and order processing modules. The end-to-end fulfilment cycle's customs clearance, payment, logistical services, and expedited delivery are shown in the lower portion.

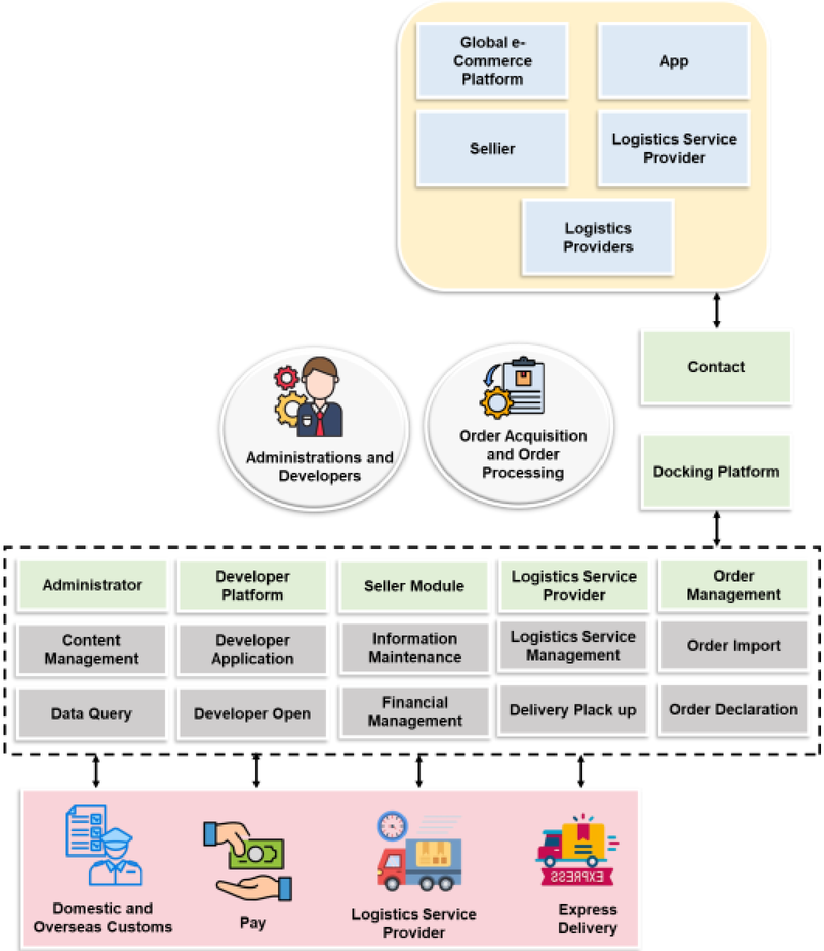

Figure 1: The cross-border e-commerce ecosystem's overall architecture

Demand ambiguity is a major problem for cross-border e-commerce businesses because inconsistencies between market demand and procurement choices create hazards all the way through the supply chain [8]. Supply chain management is the scientific approach to the development, delivery, and marketing of products, and it effectively integrates suppliers, manufacturers, and distributors to minimize total costs and maximize customer service needs [9]. "Product push" in e-commerce describes the active distribution of marketing communications to customers through subscription channels, such as emails and short messaging services. The push notification process has two forms depending on the functional differences, namely the transactional and marketing categories [10]. The volume and variability of the transaction information, and the complexity of the global online retail market create several impacts on the accuracy of the sales predictions. As such, the precision of the e-commerce firms' predictions of the sales remains difficult to enhance [11]. Cross-border e-commerce has drawn attention as a novel kind of international trade because of the complex background of the global trading environment. When combined with constructive policy methods and goals, studies of international e-commerce become more beneficial [12]. Consumers in the international market have entirely different demands and purchasing behaviors. Therefore, product development and product selection feature prominently in cross-border e-commerce enterprises [13]. It is an imperative requirement that the online retailers must be able to deliver fast service to their international customers to enhance their cross-border business.The aspects of improved delivery and refund policies attract sellers to many of the popular platforms [14].

Problem statement

Massive, diverse browsing and transaction data is produced by cross-border e-commerce platforms, but current forecasting algorithms are unable to account for intricate user-product interactions, temporal purchase patterns, and dynamic market swings. Due to their lack of flexibility, most machine learning techniques produce substandard accuracy and poor generalization across a variety of foreign marketplaces. An accurate product sales estimates for international e-commerce settings, an intelligent, scalable, optimization-driven framework that handle noisy, high-dimensional data are produced, while successfully models desperately needed relational relationships.

1.1.Objective of the research

The primary objective of this research is to design and validate a Dynamic Tangent Search–driven Graph Neural Network (DTS-GNN) for accurate and reliable product sales forecasting in cross-border e-commerce environments. Specifically, the study aims to:

- Model complex and dynamic user–product interaction patterns using graph-based representation learning.
- Reduce noise and dimensionality in large-scale browsing and transaction data through PCA-based feature extraction.
- Enhance forecasting accuracy and convergence stability by adaptively optimizing graph weights and hyperparameters using Dynamic Tangent Search.
- Evaluate the effectiveness of the proposed DTS-GNN framework against existing forecasting models using standard error, correlation, reliability, and uncertainty metrics.

1.2.Contribution of the research

- ✓ To efficiently replicate user-product links in cross-border e-commerce environments, the research indicates a unique DTS-GNN framework that combines graph neural networks with Dynamic Tangent Search optimization. This allows for adaptive graph weight change.
- ✓ Browsing habits, product metadata, and temporal purchase logs are included in a thorough multi-platform data collection pipeline which supports reliable pre-processing that uses PCA-based dimensionality reduction, Min–Max normalization, and one-hot encoding for effective feature representation.
- ✓ The efficacy, scalability, and interpretability of the suggested DTS-GNN architecture are validated by extensive tests on actual cross-border datasets that show better forecasting accuracy, enhanced R2 performance, and decreased prediction error when compared to current models.

2 Literature review

Table 1 summarizes key cross-border e-commerce forecasting models, highlighting their data types, learning strategies, strengths, and limitations. Most prior methods either lack dynamic relational modeling, struggle with noise, or are computationally heavy. The proposed DTS-GNN overcomes these gaps by combining GNNs with Dynamic Tangent Search for multi-hop relational learning and adaptive optimization.

Table 1: Comparative Summary of Reviewed State-of-the-Art Research in Cross-Border E-Commerce Sales Forecasting

Ref.	Method / Model	Primary Focus	Data Type	Optimization Strategy	Key Limitation / SOTA Gap
[15]	DL-based evaluation	Enterprise performance	Structured business data	Deep learning	Not designed for sales forecasting
[16]	Grey Models (GM)	Market growth prediction	Macro-economic data	Statistical modeling	Cannot capture dynamic user behavior
[17]	Data fusion system	Decision intelligence	Multi-source big data	Fusion algorithms	Scalability & heterogeneity challenges
[18]	Stackelberg game model	Platform strategy	Strategic variables	Game theory	Simplified assumptions; no forecasting
[19]	Dynamic programming	Cold-chain inventory	Supply chain data	Risk optimization	Not user-behavior driven
[20]	Blockchain model	Trust & transparency	Transactional data	Blockchain framework	No predictive learning

[21]	Gray evaluation	Economic correlation	Provincial data	Gray theory	Macro-level only; no micro sales modeling
[22]	HFL-ConvLSTM (Horizontal Federated Learning + Convolutional LSTM)	Privacy-preserving e-commerce demand forecasting & bullwhip effect reduction	Multi-dimensional time-series sales data across enterprises	Federated model aggregation with ConvLSTM spatiotemporal feature learning	High-dimensional temporal patterns and require centralized data sharing, leading to privacy risks and poor supply-chain coordination
[23]	IoT + multi-objective model	Supply chain visibility	IoT tracking data	Multi-objective optimization	No sales forecasting architecture
[24]	Collaborative filtering	Logistics selection	Export logistics data	Similarity-based learning	No temporal dynamic modeling
[25]	Big data analytics	Aquatic supply chain	Industry-specific data	Quantitative evaluation	Domain-specific; limited scalability
[26]	AdaBoost + Decision Tree	Strategic country evaluation	Country-level data	Ensemble learning	Classification only; not sales prediction
[27]	Bi-Directional Gated Recurrent Unit (Bi-GRU)	Retail sales forecasting for E-commerce	Rossmann & Walmart benchmark datasets (time-series retail sales data)	Adaptive Particle Swarm Optimization (APSO), Recursive Feature Elimination (RFE), Minimum Redundancy Maximum Relevance (MRMR)	Requires high-quality preprocessed data; computational complexity due to multiple feature selection stages; limited cross-domain generalization evaluation
[28]	Statistical attribution model	Review–sales relationship	Platform review data	Regression/statistical	Single-factor influence modeling
[29]	DPMES	Dynamic sales prediction	Behavioral sales data	Correlation mining	Static correlations; noise sensitivity
[30]	CSA–ANN	Sales + supply chain	IoT + sales data	Capuchin Search optimization	High computation; no graph learning
Proposed	DTS-GNN	Adaptive cross-border sales forecasting	User browsing + product + temporal data	Dynamic Tangent Search + GNN	Addresses SOTA gaps via adaptive graph optimization

2.1 Research gaps

The techniques that use behavioral data and lead to better forecasting results lack adaptability when faced with changing user-item interactions and struggle when dealing with volatile sales variations. Even with modifying or polishing parameters through count and correlation mining, they fail when it comes to dealing with noisy or volatile scenarios since they tend to overemphasize either the availability of data or data quality. The increased computational difficulty and low ability to acquire user and item exchanges when optimized through meta-heuristics play a fundamental role in making ensemble learning models inferior. Then there is shallow feature representation in cross-border e-commerce, further reducing their robustness for a variety of market conditions. The suggested DTS-GNN effectively unveiled complex relationship patterns while minimizing computation, enhancing scalability, and achieving high-precision, trustworthy cross-border sales forecasting with the help of adaptive graph learning and tangent-based optimization combined with PCA-enhanced feature extraction.

2.2 Research questions

To achieve the stated objectives, this study addresses the following research questions:

- RQ1: How effectively can Graph Neural Networks capture dynamic user–product interaction relationships in cross-border e-commerce data?

- RQ2: To what extent does Dynamic Tangent Search optimization improve graph weight adaptation and forecasting accuracy compared to static optimization methods?
- RQ3: How does PCA-based feature reduction influence model stability, scalability, and prediction performance in high-dimensional browsing datasets?
- RQ4: Does the proposed DTS-GNN framework outperform existing sales forecasting models in terms of MAE, RMSE, MAPE, correlation, reliability, and uncertainty measures?

3 Methodology

To provide optimal input to DTS-GNN, the proposed methodology uses multi-platform data fetching techniques that are coupled with in-depth pre-processing and advanced feature engineering techniques. Compact and better feature spaces are achieved through noise elimination techniques, imputation techniques, normalization techniques, and PCA. GNN are employed to capture relational user-product graphs, and better representation learning along with higher accuracy in cross-border ecommerce sales prediction are achieved using DTS. Figure 2 illustrates the sequential process of multi-platform data acquisition, data preprocessing (noise removal, missing value handling, Min–Max normalization, and one-hot encoding), PCA-based feature extraction, construction of the user–product interaction graph, and adaptive optimization of graph weights using DTS, culminating in accurate product sales prediction.

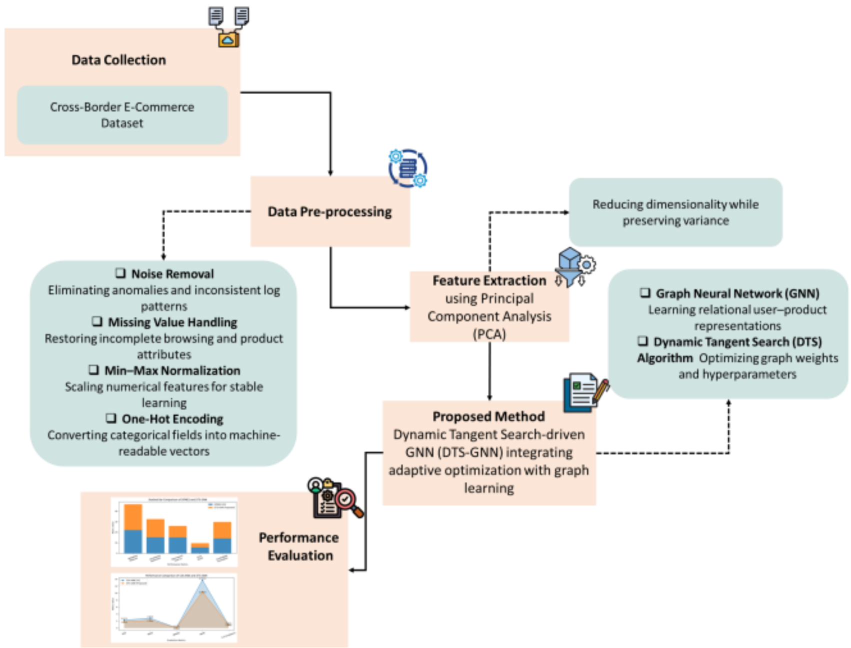

Figure 2: Overall methodology workflow of the proposed DTS-GNN framework for cross-border e-commerce sales forecasting.

3.1 Data acquisition

The dataset used in the research, the Cross-Border E-Commerce Dataset, contains 2,100 records collected from various e-commerce platforms, offering valuable information on user sessions, product descriptions, and temporal purchase records. It includes features such as user demographics, session activity, product metadata (e.g., price, discount rate, ratings), and transactional histories, with key attributes including user ID, activity level, session count, product ID, price, review count, and sales volume. The dataset is publicly available on Kaggle and can be accessed via this link https://www.kaggle.com/datasets/programmer3/cross-border-e-commerce-dataset. Preprocessing involves several critical steps to prepare the data for modeling. These include noise removal, where outliers and inconsistent records are eliminated using statistical methods like Z-scores and IQR. Missing values are handled through adaptive interpolation for numerical data and mode-based imputation for categorical data. Min-Max normalization scales numerical features to a range of [0, 1], ensuring stable model learning. One-hot encoding is used for categorical variables, removing ordinal bias and ensuring that each feature is treated independently. Additionally, PCA is applied for dimensionality reduction, retaining the most significant features and enhancing model efficiency. These preprocessing techniques ensure the dataset is clean, normalized, and optimized for use in the DTS-GNN model, improving the accuracy and generalization of the sales forecasting predictions. The dataset was divided into training (70%), validation (15%), and testing (15%) subsets at random. The test set assessed the performance of the finished model, while the validation set was utilized for hyperparameter adjustment and early stopping to avoid overfitting. Table 2 represents the dataset key features description.

Table 2: Key Features of the Cross-Border E-Commerce Dataset

Feature Name	Description
user_id	Unique identifier for each user
user_activity_level	Activity intensity of the user (1–10)
session_count	Total browsing sessions by the user
avg_session_duration	Average session duration (seconds)
buyer_region_code	Code representing the buyer's region
product_id	Unique identifier for each product
category_code	Product category identifier
price	Product price
discount_rate	Applied discount rate (0.0–0.6)
product_rating	Average product rating
review_count	Number of customer reviews
dwell_time	Time spent on product page (seconds)
click_count	Number of clicks per session
scroll_depth	Page scroll proportion (0.1–1.0)
add_to_cart	Added to cart flag (0/1)
wishlist_flag	Added to wishlist flag (0/1)
interaction_frequency	Total user–product interactions
recency_score	Recent interaction score (0.0–1.0)
seasonal_index	Seasonal demand factor (0.7–1.3)
quantity_sold	Target variable – units sold

3.2 Data pre-processing

Data pre-processing normalizes raw cross-border e-commerce data by removing variance, standardizing feature scales, and encoding categorical variables. All features should be represented consistently with one-hot encoding, Min-Max scaling, noise filtering, and missing value imputation. Furthermore, such a structured transformation generates high-quality inputs for DTS-GNN training by not only lowering variance and improving model stability but also guaranteeing the quality of inputs.

3.2.1 Noise removal

Noise reduction is a technique used before training a model to make the data used by cross-border e-commerce browsers and transactions more reliable to a significant extent. Inconsistent timestamp records, incorrect logs, and repeating user sessions are eliminated first. The technique involves the use of the Z-score value thresholds as well as the Interquartile Range, or IQR, to clean outlier payments, unusual browsing times, and the sudden surge in the number of mouse clicks. In adaptive imputations, there is the identification and correction of incomplete interaction records, resulting from system errors, to make the data used

more reliable to a large extent because adaptive imputations are used to identify and correct incomplete interaction records resulting from system errors.

3.2.2 Missing value handling for restoring incomplete browsing and product attributes

During the input of data in the DTS-GNN model, missing value processing is performed to ensure that the data is full and maintains the integrity of user-product interaction patterns. Based on distribution features, adaptive statistical methods-based interpolation is used to infer numerical parameters such as browsing duration, product views, and session intervals. To maintain semantic consistency, the categorical elements including product category, user device type, or session source are filled based on mode-based or frequency-aware imputation. Time-series gaps in browsing sequences are rebuilt via forward-backward filling to maintain temporal continuity. This strong imputation technique can avoid feature distortion and overall forecasting accuracy improvement, stabilizing the learning process.

3.2.3 Min–Max normalization for scaling numerical features for stable learning

Min-Max Scaling is applied to normalize the multi-dimensional attributes extracted from the cross-border ecommerce users' browsing history, product details, and sales data over time. The learning of stable models is also dependent on the normalization of important attributes like click rates, viewing times, product prices, and the sales history of many users to a uniform scale due to the large differences in their magnitudes. By normalizing the values of the multi-dimensional attributes to the range of [0,1] values, the Min-Max normalization approach ensures that the inherent relational patterns contained in the attributes and the dominant impact of attributes with large magnitude in the learning phase are well preserved. The DTS-GNN is considerably influenced by the difference in the dimensions of the attributes in the learning of the representation and the optimization phase. Well-tempered learning and adaptation of the weights in the learning phase of the models and the learning of the relational patterns of users and the items they interact with in a dependable way is guaranteed. Mathematically, the Min-Max normalization can be expressed using the below formula (1):

$$\mathrm{w}' = \frac{\mathrm{w}-\mathrm{min}_A}{\mathrm{max}_A-\mathrm{min}_A}(\mathrm{new\_max}_A - \mathrm{new\_min}_A) + \mathrm{new\_min}_A \quad (1)$$

Where, $\mathrm{new}_{\mathrm{max}_A}$ and $\mathrm{new\_min}_A$ define the new range, min_A and max_A are the lowest and maximum calculated values of feature A, and w' is the normalized value and w is the primary value. The stability, accuracy, and interpretability of the suggested DTS-GNN architecture for cross-border product sales forecasting are improved by using this scaling technique, which guarantees browsing, behavioural, and transactional characteristics to contribute proportionately.

3.2.4 One-hot encoding- converting categorical fields into machine-readable vectors

Categorical properties are coded into a binary vector readable to machines via one-hot encoding to remove ordinal bias. Product type, consumer region, device platform, and session origin are some homogeneous properties that are coded into different binary attributes within a sparse vector space. This ensures that all categorical properties are treated as exclusive entities within the DTS-GNN framework and that inaccurate distance associations are not generated from coded labels. Sparse matrix coding is applied to enhance all computational operations involved in coding and to remove overhead in dealing with large e-commerce transactions involving border aspects. Binary properties reduce inaccuracy in sales prediction.

3.3 Principal component analysis (PCA) for feature extraction

In the research, the key behavioral, transactional, and product-related characteristics are mined from voluminous cross-border e-commerce datasets using PCA. The aim is to reduce the dimensionality and processing overhead while capturing the striking patterns in user browsing sessions, product interactions, and temporal buying habits. By maintaining the components with the greatest explanatory variance, PCA enhances the learning of DTS-GNN and ensures the preservation of major browsing frequency patterns, product affinity scores, and session level dynamics. Mathematically, Equation (2) is presented as follows:

$$\mathrm{Y}_{ij} = \mathrm{d}_{i1}\mathrm{w}_{1j} + \mathrm{d}_{i2}\mathrm{w}_{2j} + \mathrm{d}_{i3}\mathrm{w}_{3j} + \cdots + \mathrm{d}_{in}\mathrm{w}_{nj} \quad (2)$$

In this case, Y_{ij} stands for the principal component score for performance i, d_{in} for the loading values, w_{nj} for the regular input variable, j for the factor index, and n for the total number of variables. To enhance interpretability, factors with eigenvalues larger than one are maintained and turned using the varimax approach. This reduced redundancy while preserving vital behavioural information essential for exact sales prediction in the DTS-GNN framework by guaranteeing that browsing depth, clickstream frequency, product-level characteristics, and temporal purchase indicators were strongly related with distinct principal components.

3.4 Dynamic tangent search-driven graph neural network (DTS-GNN) integrating adaptive optimization with graph learning

To enhanced adaptation on the interactions between the user and the product, the DTS-GNN integrates graph representation learning. It also includes a layer of Dynamic Tangent Search for the purpose of optimization. Though the DTS applies the use of tangent search exploration-exploitation search for the adaptation of graph weights and hyperparameters, the GNN achieves the embedding of multi-hop relations. The optimization here achieves the optimal graph structure finding that resulting adaptive optimization. This amalgamated architecture adds more precision on the forecasts of the cross-border e-commerce sales.

3.4.1 Graph Neural Network (GNN) for learning relational user–product representations

In the GNN framework, each user and product node starts with initial features, such as browsing frequency or product attributes. During training, the network propagates information across the graph to update these features. This allows the model to capture complex relationships between users and products by learning multi-hop dependencies.

$$h_i^{(k+1)} = \sigma(\textstyle\sum_{j\epsilon N(i)} w^{(k).h_j^{(k)}} + b^{(k)} \quad (3)$$

The equation (3) represents the updated feature vector $h_i^{(k+1)}$ of node i at iteration $k+1$, where it aggregates the features $(k+1)$ of its neighboring nodes $j\epsilon N(i)$ with a weight $w^{(k)}.h_j^{(k)}$ for each edge. The sum is passed through an activation function σ, and a bias term $b^{(k)}$ is added to adjust the output. This update enables node iii to learn from its neighbors' features.

The feature vectors of every node next to z_i are represented by the term $w_{ne(i)}$, which captures contextual browsing and interaction signals. The feature vectors of edges which relates node v_i, such as click intensity, time gaps, or purchase transitions that specify user–product connections, are referred to as $z_{co(i)}$. The model integrates multi-hop relational information at each update step, since the component $g_{ne(i)}^{s-1}$ reflects the collection of embedding vectors of surrounding nodes from the previous iteration. When combined, these inputs enable the GNN to represent intricate cross-border user-product interaction patterns through an organized and effective propagation mechanism. Figure 3 represents the structure of GNN.

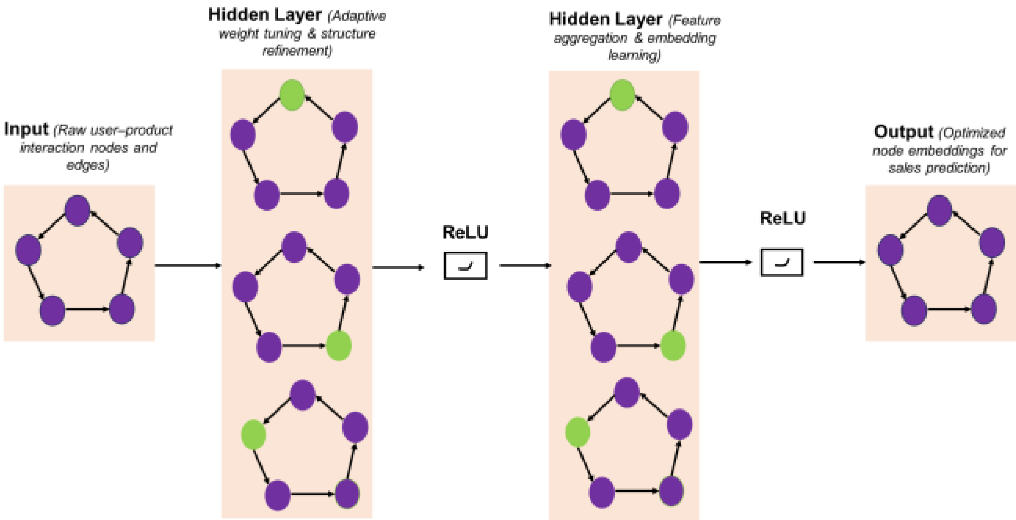

Figure 3: Structure of Graph Neural Network (GNN)

3.4.2 Dynamic Tangent Search (DTS) algorithm optimizing graph weights and hyperparameters

The DTS works by generating a set of random solutions for the graph weights and hyperparameters. It then refines these solutions through a series of local adjustments (intensification) and broader searches (exploration). This process helps avoid suboptimal solutions, improving the model's ability to predict sales accurately, especially in dynamic market conditions. A key feature of DTS is its ability to avoid getting stuck in local minima by using an escape mechanism, which ensures that the algorithm continues to evolve towards the best possible solution. This is achieved by adjusting the step size and introducing controlled perturbations, which maintain the balance between discovering new solutions and refining existing ones. By integrating these dynamic optimizations, DTS contributes to more accurate and reliable product sales forecasting by continually adapting to changes in user behavior and sales trends.

Figure 4 ETSA starts by initializing a population and applying fitness-weighted search with opposition-based learning. Based on a switching mechanism, it alternates between exploration and intensification to balance global and local search. An escape strategy avoids local minima, and the process repeats until the end condition is satisfied.

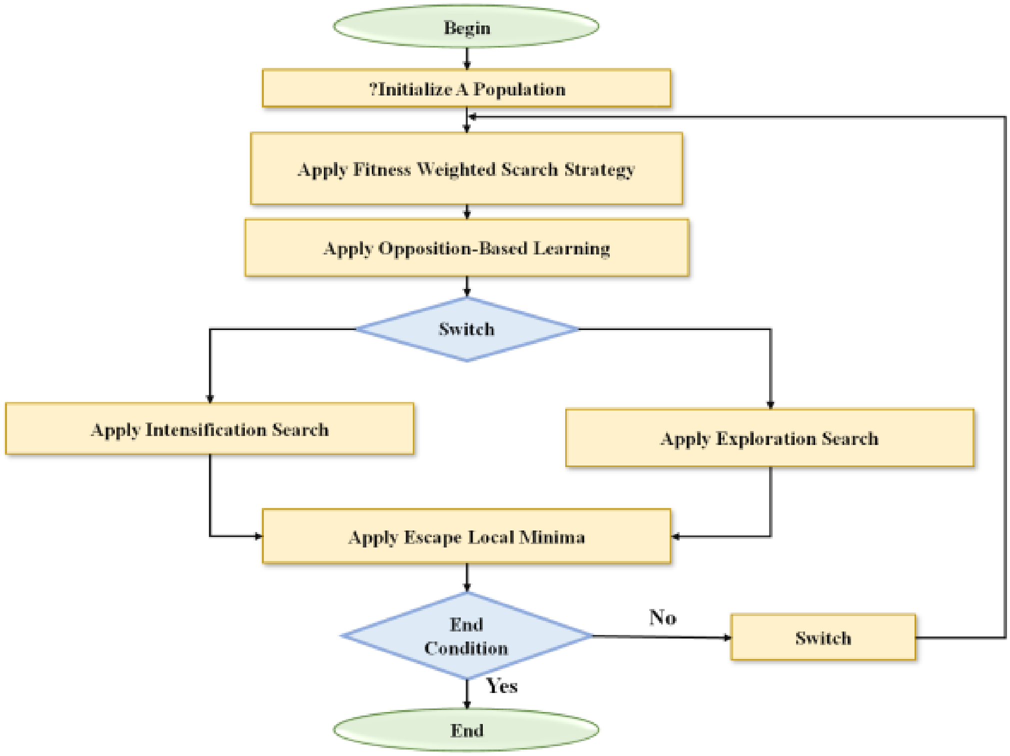

Figure 4: Flowchart of the DTSA adaptive exploration–exploitation and local minima avoidance

The capacity to traverse from $-\infty$ to $+\infty$, which facilitates the effective identification of ideal graph topologies that improve sales, forecast accuracy and user-product connection learning.

- **Initialization**

TSA initializes a population of potential graph-weight vectors and hyper-parameter sets in the DTS-GNN configuration using equation (5):

$$Z_0 = l + (u - l) \cdot \mathrm{rand}() \quad (5)$$

In this case, rand() generates uniformly distributed random numbers, while, l and u stand for the bottom and upper boundary of graph weight values. Z_0represents the initial solution (or initial position) generated for the optimization process. This creates a varied search population to improve scalar learning coefficients and adjacency weight values.

- **Intensification Search (Exploitation Phase)**

The intensification step enhances the quality of node-embedding propagation in GNN layers by fine-tuning graph weights around promising locations. A tangent-driven local walk is carried out by each potential solution in equation (6):

$$Z_i^{s+1} = Z_i^s + \mathrm{stepsize1} \cdot \tan(\theta) \cdot (Z_i^s - Z_{best}^s), \quad i = 1, \dots, M \quad (6)$$

The current solution at iteration s in this equation is denoted by Z_i^s, whereas the best-performing solution in the population is denoted by Z_{best}^s, and Z_i^{s+1} represents the updated solution vector and M denotes the population size. While the extent of exploitation is determined by stepsize1, the term $\tan(\theta)$ introduces controlled disturbances. The solution is guided toward locally optimum graph-weight areas by this update. The relevant values from the current best solution are substituted for a subset of the variables (20% for high-dimensional graphs, 50% for low-dimensional feature sets) in equation (7):

$$Z_i^{s+1} = Z_{best}^s \quad \text{if variable i is selected} \quad (7)$$

Exploitation is guided by the following equation (8) step size:

$$\mathrm{stepsize1} = 10 \cdot \mathrm{signum}(\mathrm{rand} - 0.5) \cdot \mathrm{norm}(Z_{best}^s) \cdot \log\left(1 + \frac{10D}{s}\right) \quad (8)$$

In this case, the Euclidean norm of the optimal solution is calculated by norm(·), which reflects its magnitude. Direction is randomized by the phrase signum $(\mathrm{rand} - 0.5)$ signum, and the dimensionality of the optimization problem is represented by D. Stable convergence is ensured by the logarithmic term, which progressively reduces the step size. This preserves the variety by enabling DTS to strengthen around robust GNN setups. If a solution exceeds the allowed graph-weight boundaries in equation (9), correction is applied:

$$Z = \mathrm{rand} \cdot (u - l) + l \quad (9)$$

Any out-of-range solution is reset into the feasible domain using this boundary-control equation. The permitted range is once more defined by the parameters l and u, and stochastic reinitialization is guaranteed by rand.

- **Exploration Search (Global Search Phase)**

Through exploration, DTS-GNN find different graph topologies and prevent training stagnation. A step of global tangent-driven search is carried out in equation (10):

$$Z_i^{s+1} = Z_i^s + \text{stepsize2} \cdot \tan(\theta) \tag{10}$$

In this case, $\tan(\theta)$ disperses solutions extensively over the search space, whereas stepsize2 controls the extent of global investigation. By allowing significant leaps to uncharted graph topologies, this step boosts variety. The calculation of the global step size is in equation (11):

$$\text{stepsize2} = 1 \cdot \text{signum}(\text{rand} - 0.5) \cdot \text{norm}(\text{opt}Z^s - Z_i^s) \cdot \log(20 + s) \tag{11}$$

In this formula, the globally optimal solution discovered thus far is represented by $\text{opt}Z^s$. The Euclidean distance $\text{norm}(\text{opt}Z^s - Z_i^s)$ ensures that the exploration intensity is dependent on the distance of a solution from the optimum. The exploration activity is scaled across iterations by the logarithmic term. This technique enhances GNN generalization for cross-border behavioural patterns by introducing substantial structural variety in the adjacency matrix and feature transformation parameters. Each iteration's intensification or exploration is determined by a switching parameter, $Q_{switch} \in [0,1]$.

- **Local Minima Escape Procedure**

A structured escape procedure is carried out with probability Q_{esc} to stop DTS-GNN from prematurely converging to suboptimal graph weights:

One of the following equations (12) actions is carried out if a potential solution is chosen:

$$Z_i^{s+1} = Z_i^s + T \cdot (\text{opt}Z^s - \text{rand} \cdot (\text{opt}Z^s - Z_i^s)) \tag{12}$$

The displacement strength is adjusted by the term T, the solution is pulled toward promising areas by the term $\text{opt}Z^s$, and predictable pathways are avoided by adding randomization with the term rand.

Where,

$$T = \frac{10 \cdot \text{sign}(0.5 - \text{rand})}{\log(1 + s)} \tag{13}$$

To preserve stability while permitting controlled perturbations, the coefficient T declines over iterations (Equation 13). The logarithmic denominator guarantees decreasing volatility as convergence advances, but the sign term randomizes the direction of movement. In addition to this, by encouraging the investigation of novel graph-learning configurations pertinent to cross-border user-product interactions, this approach effectively moves the model away from subpar local optima.

- **Parameter Explanation**

The balance between exploration, which searches for new graph structures, and exploitation, which fine-tunes graph weights, is determined by the parameter Q_{switch}. In a similar vein, Q_{esc} regulates the frequency of escape operations that prevent the model from getting trapped in local minima. To stabilize the optimization process and guarantee the smooth convergence of graph-weight updates, the dynamic step-size parameters, step1 and step2, progressively decrease over iterations. The severity of tangent-based perturbations is controlled by the angle parameter θ; so that the greater values result in more notable structural changes in the graph. Algorithm 1 represents the Dynamic Tangent Search–driven Graph Neural Network (DTS-GNN) algorithm.

Algorithm 1: Dynamic Tangent Search–Driven Graph Neural Network (DTS-GNN)

$$Input: \ Cross - Border\ E - Commerce\ Dataset$$

$$Output: Optimized\ DTS - GNN\ model\ X*$$

$$1: \ Load\ cross - border\ e - commerce\ dataset$$

$$2: \ Initialize\ GNN\ parameters\ (weights, learning\ rate, embeddings)$$

$$3: \ Initialize\ DTS\ parameters\ (population\ size\ M, step\ size\ \alpha, angle\ \theta)$$

$$4: \ Perform\ data\ pre - processing$$

$$- Noise\ removal$$

$$- Missing\ value\ imputation$$

$$- Min - Max\ normalization$$

$$- One - hot\ encoding$$

$$5: \ Apply\ PCA\ to\ extract\ reduced\ feature\ set$$

6: Construct user–product interaction graph G = (V, E)

7: $Initialize\ DTS\ population$

$for\ i\ =\ 1\ to\ M\ do$

$Zi^0\ =\ l\ +\ (u\ -\ l)\ \times\ rand()$

$end\ for$

8: $for\ t\ =\ 1\ to\ T\ do$

9: $Compute\ adaptive\ step\ size\ \alpha(t)$

10: $Forward\ propagate\ node\ features\ through\ GNN$

11: $Aggregate\ multi-hop\ neighbor\ information$

12: $Update\ GNN\ weights\ using\ gradient\ descent$

13: $for\ each\ DTS\ solution\ Zi\ do$

14: $Update\ solution\ using\ tangent\ search$

$Zi(t+1)\ =\ Zi(t)\ +\ \alpha(t)\ \times\ tan(\theta)\ \times\ (Zi(t)\ -\ Zbest(t))$

15: $Apply\ boundary\ control\ on\ Zi(t+1)$

16: $end\ for$

17: $If\ stagnation\ detected\ then$

18: $Apply\ local-minima\ escape\ strategy$

19: $end\ if$

20: $Predict\ product\ sales\ using\ optimized\ GNN\ embeddings$

21: $Evaluate\ fitness\ (MAE, RMSE, Correlation, Search\ Time)$

22: $Update\ global\ best\ solution\ Zbest\ if\ fitness\ improves$

23: $Reduce\ step\ size\ \alpha(t)\ for\ convergence\ stability$

24: $end\ for$

25: $Return\ optimized\ DTS-GNN\ model\ X*=\ Zbest$

The suggested DTS-GNN models intricate the user-product interactions in international e-commerce by combining Graph Neural Networks with Dynamic Tangent Search optimization. To improve relational learning, DTS adaptively adjusts graph weights and hyper-parameters following thorough data pre-processing and PCA-based feature extraction. This optimization-driven system enables precise, trustworthy sales forecasting under changing market conditions, which enhances convergence stability, and captures multi-hop dependencies. Table 3 represents the Hyper-parameter settings used for the proposed DTS-GNN model.

4 Performance evaluation

The experimental findings show that the suggested DTS-GNN regularly performs better than current

Hyper-parameter	Symbol	Description	Typical Value
Learning rate	η	Controls GNN weight updates	0.001
Number of GNN layers	L	Depth of graph message passing	2–4
Hidden units	H	Neurons per GNN layer	64
Batch size	B	Samples per training iteration	32
DTS population size	P	Number of candidate solutions	20
Max iterations	T	Optimization iterations	100
Tangent angle	θ	Controls search perturbation	(0, π/2)
Step size	α	DTS adaptive update factor	0.1
PCA components	K	Retained principal components	10–20

forecasting models on a variety of assessment parameters. By enhancing the prediction accuracy, convergence speed, and resilience, its adaptive graph optimization successfully captures dynamic user-product interactions in intricate cross-border e-commerce contexts.

4.1 Experimental setup

The experiment uses the TensorFlow ML framework and the Python programming language to develop the DTS-GNN algorithm on a server with an NVIDIA GeForce RTX 3090 GPU, an Intel Core i9-11900K CPU, and 32GB of RAM.

To further validate the effectiveness of the proposed DTS-GNN model, we recommend including additional baseline models for comparison. While the current comparison with models like DPMES and CSA-ANN demonstrates

improvements in key metrics (e.g., MAE, RMSE, MAPE), incorporating more industry-standard models could better highlight the advantages of the DTS-GNN in handling dynamic user-product interactions and high-dimensional data in cross-border e-commerce.

The suggested DTS-GNN model's training and validation results across 300 epochs are shown in the figure 5. Figure 5(a) Effective learning is shown by the accuracy plot's quick convergence, high training accuracy, and steady validation accuracy. Figure 5(b) Training loss is sharply reduced in the loss plot, whereas validation loss first declines and then progressively rises, indicating strong convergence with slight overfitting control.

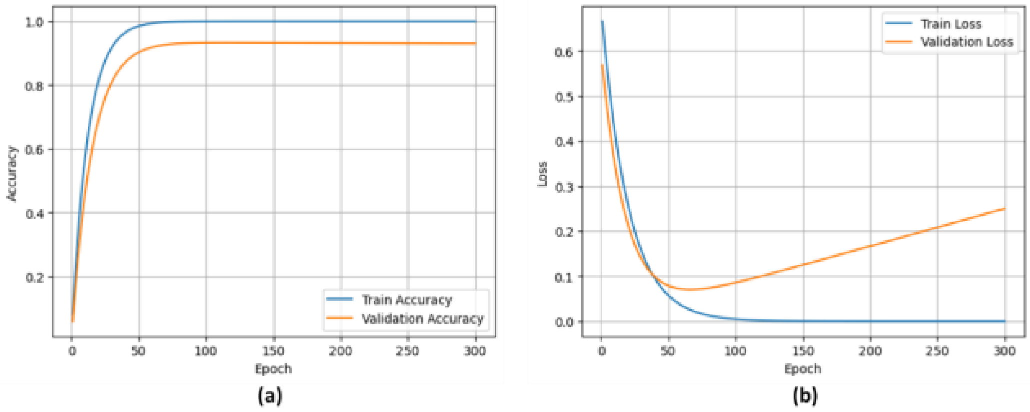

Figure 5: (a) Training and validation accuracy curves of the proposed DTS-GNN model across epochs, and (b) Training and validation loss curves over epochs

Figure 6 displays two three-dimensional depictions of cross-border e-commerce data links. Figure 6(a) highlights dense interaction patterns and wide sales variability by illustrating how product pricing and user dwell duration simultaneously affect the amount sold. A synthetic sales-related indicator as a function of price and discount rate is shown in figure 6(b), which reveals non-linear demand trends and areas of stronger sales responsiveness under particular pricing–discount combinations.

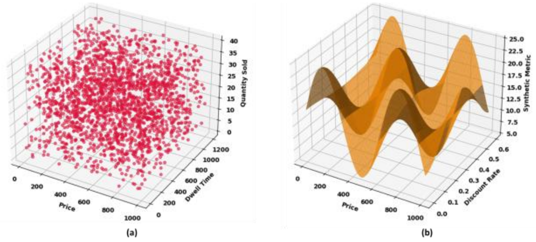

Figure 6: Graphical representation of (a) price–dwell time–quantity sold relationships and (b) price–discount rate influence on a synthetic sales metric in cross-border e-commerce

Figure 7 displays the Andrews curves which are used to illustrate high-dimensional cross-border e-commerce attributes after modification. By representing each observation as a continuous function, each curve makes it possible to identify distribution patterns, similarity, and variability among feature sets. Complex non-linear interactions and clustering tendencies within user browsing and product interaction data are indicated by the overlapping curves.

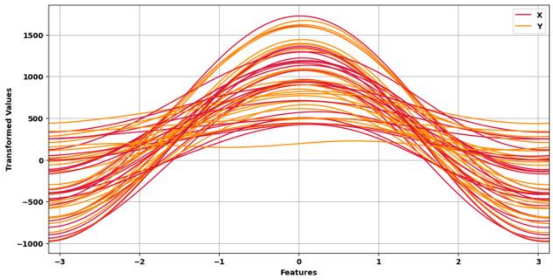

Figure 7: Representation of transformed cross-border e-commerce feature distributions

Multiple experimental visualizations of cross-border e-commerce data are shown in Figure 8. Figure 8(a) depicts the impact of product pricing on quantity sold, where the user click intensity and engagement variability are represented by bubble density. The distribution of user attention across product pages is shown in Figure 8(b), which highlights a variety of browsing habits. Variations in promotional tactics among samples are depicted in Figure 8(c), which shows an erratic discount pattern that affect consumer choices.

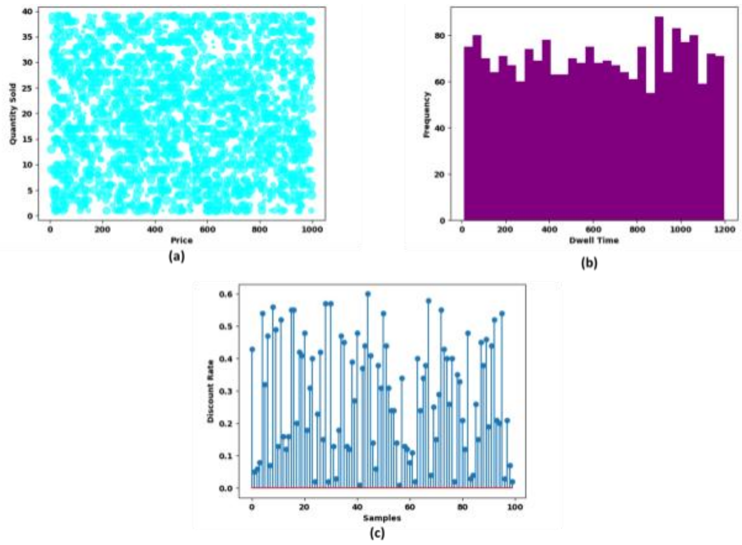

Figure8: Exploratory analysis of (a) price–click influence, (b) dwell time distribution, and (c) discount rate variation in cross-border e-commerce data

Two graphic evaluations of price impacts in cross-border e-commerce are shown in Figure 9. The distribution and concentration of the amount sold across different price points are shown in Figure 9(a), which reveals a dense sales regions and wide demand fluctuation. Figure 9(b) illustrates the extent of price reductions and their impact on relative sales positioning and consumer purchasing incentives by contrasting original product prices with reduced prices for sampled goods.

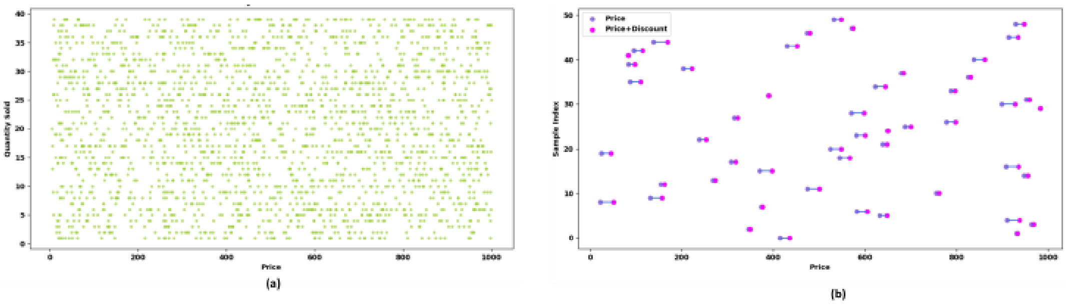

Figure 9: Analysis of (a) sales distribution and (b) discount impact in cross-border e-commerce

Three complementary visualizations for examining price-sales correlations in international e-commerce are combined in Figure 10. Regions with high and low sales concentration at various price points are shown in Figure 9(a). The dissimilarity levels between feature vectors, which exhibit data diffusion and clustering tendencies, are shown in Figure 10(b). The wide dispersion is seen in Figure 10(c) which reflects a variety of customer reactions to pricing tactics as well as non-linear demand dynamics.

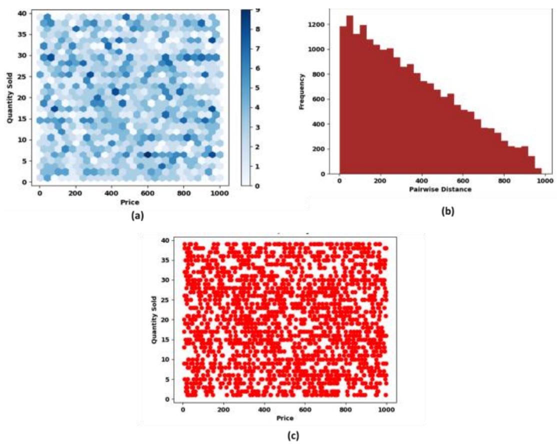

Figure 10: (a) Hexbin density, (b) pairwise distance distribution, and (c) scatter analysis of price–sales dynamics

The dataset's variations in quantity sold over successive samples are shown in Figure 11. The filled regions highlight the fluctuations in sales intensity, exposing erratic demand trends, abrupt declines, and sharp peaks. The requirement for adaptive forecasting models to capture dynamic sales behaviour is supported by this graphic, which emphasizes temporal volatility.

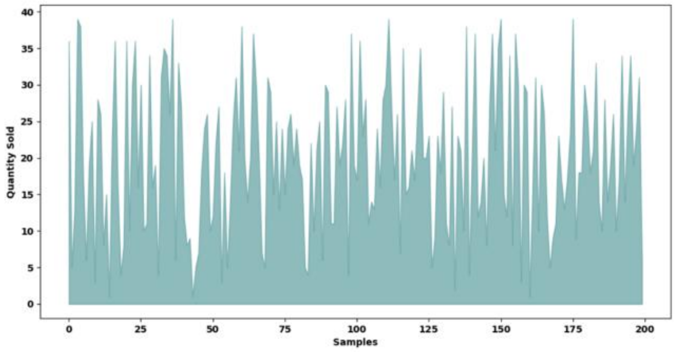

Figure 11: Temporal variation in product sales across cross-border e-commerce samples

Multivariate connections among price, amount sold, dwell duration, and discount rate for two sample groups are shown in Figure 12. A product instance is represented by each polyline, which shows the differences and correlations between characteristics. In cross-border e-commerce analysis, the figure illustrates how the changes in price and user engagement measures jointly affect sales outcomes.

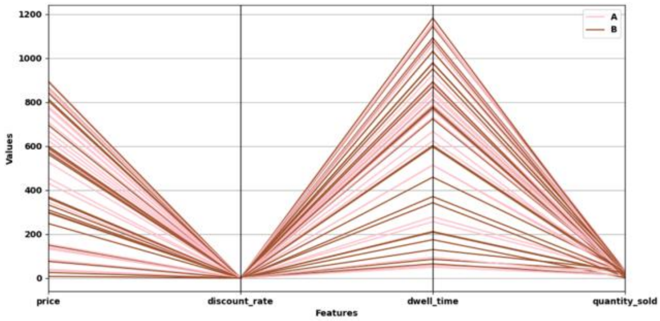

Figure 12: Multi-featured relationships influencing product sales in a cross-border e-commerce dataset

Figure 13 shows how consumers' recent interactions with items on the platform are reflected in differences in recent ratings across subsequent samples. The stepwise pattern captures short-term behavioural dynamics that are essential for modelling user interest, setting suggestion priorities, and increasing the accuracy of sales forecasts by highlighting sudden variations in interaction intensity over time.

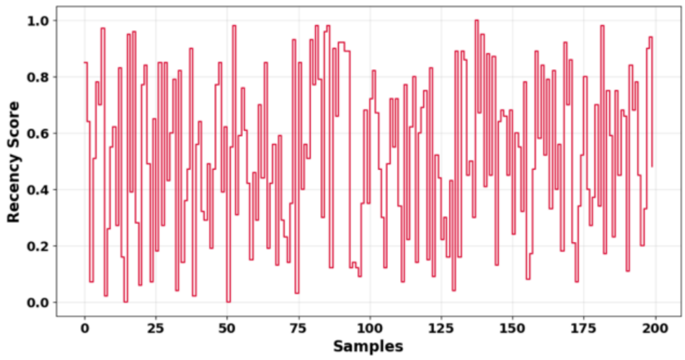

Figure 13: Temporal variation in user interaction recent scores across samples

A ridgeline density map showing the distribution of quantity sold across seven categories is shown in Figure 14. The probability density of each category is shown by a coloured curve that highlights differences in sales dispersion, central tendency, and overlap. Comparative examination of sales behaviour is made possible by the plot, which highlights both similarities and variations in demand patterns between categories.

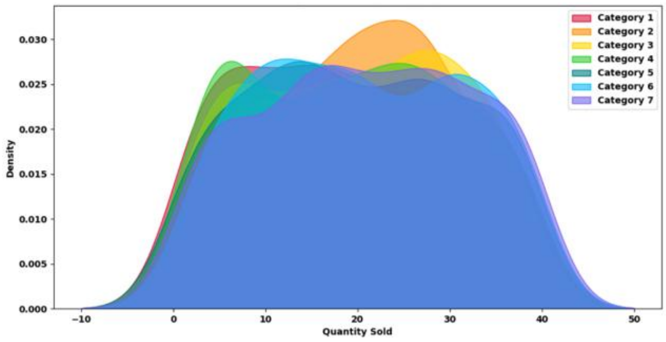

Figure 14: The distribution of quantity sold across seven product categories

A stacked area plot showing sales and cart-related statistics across several samples is shown in Figure 15. Consistent growth throughout time is seen by the cumulative area's constant upward trend. The combined contribution of sales and cart activity is represented by overlapping shaded patches, highlighting their general accumulation pattern and progressive rise.

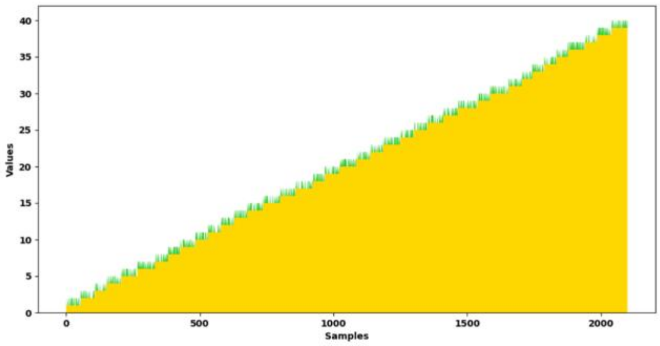

Figure 15: Cumulative sales and cart values across sequential samples

4.2 Comparative analysis

The suggested DTS-GNN outperforms the Dynamic Prediction Model for E-Commerce Sales (DPMES) [29] and Capuchin Search Algorithm–based Artificial Neural Network (CSA-ANN) [30] in terms of predicting performance in terms of MAE, RMSE, NRMSE, MAPE, correlation, reliability, and uncertainty measures. Under complicated and changing market conditions, its adaptive graph learning and dynamic tangent optimization allow more reliable, accurate, and consistent cross-border sales forecasts.

Compared with recent state-of-the-art models such as DPMES and CSA-ANN, the proposed DTS-GNN demonstrates clear superiority in accuracy, convergence speed, and robustness. While existing SOTA models primarily rely on static correlation mining or metaheuristic-optimized neural networks, DTS-GNN uniquely combines adaptive graph representation learning with dynamic tangent-based optimization, enabling effective capture of evolving user–product relationships in cross-border e-commerce. This architectural advantage explains the consistent performance gains observed across all evaluation metrics.

- **Reliability Measure:** The model's consistency in predicting sales over a range of cross-border browsing habits, goods, and time periods is indicated by the reliability measure. Increased dependability demonstrates that DTS-GNN sustains steady performance in the face of shifting user behaviour and market conditions.
- **Uncertainty distinction:** Uncertainty Distinction evaluates how well the model uses browsing cues to distinguish between high-confidence and low-confidence predictions. In cross-border platforms, effective distinction guarantees that DTS-GNN correctly captures noise, unpredictability, and unclear user-product interaction patterns.
- **Best search time (s):** During dynamic tangent optimization, Best Search Time (s) is the least amount of time that the DTS-GNN needs to arrive at the ideal graph-weight configuration. Large-scale cross-border e-commerce datasets are handled more effectively and with faster convergence when the values are lower.
- **Error factor:** After simulating browsing characteristics, interactions, and temporal behaviours, the error factor measures the difference between anticipated and actual

product sales. Improved prediction accuracy using dynamic graph learning is shown in a decreased error factor.

- **Controllable Correlation:** The model's ability to capture and control correlations between browsing habits, product relationships, and purchase patterns is measured by Controllable Correlation. DTS-GNN learns significant structural dependencies for accurate cross-border sales forecasting, as demonstrated by a higher controlled correlation.

Table 4 and Figure 16 (a) represent a performance comparison between the existing DPMES model and the proposed DTS-GNN framework across key evaluation metrics.

Table 4: Performance comparison between the existing DPMES model and the proposed DTS-GNN framework across key evaluation metrics

Metrics	DPMES [29]	DTS-GNN [Proposed]
Reliability measure	22.0	24.6
Uncertainty distinction	15.1	17.3
Best search time (s)	15.0	10.9
Error factor	5.5	4.1
Controllable correlation	14.0	15.8

- **Mean Absolute Error (MAE):** MAE is a measure of the average absolute difference between planned and actual sales values. A lower MAE means that the DTS-GNN with little prediction variance captures user browsing activity and product interaction patterns accurately.
- **Root Mean Square Error (RMSE):** RMSE emphasizes greater errors by quantifying the square root of the average squared prediction errors. DTS-GNN successfully predicts the complicated cross-border browsing data and non-linear sales trends, as demonstrated by reduced RMSE.
- **Normalized RMSE (NRMSE):** By normalizing RMSE in relation to data scale, NRMSE enables an equitable comparison between various product categories. A lower NRMSE indicates that DTS-GNN consistently maintains accuracy in a variety of cross-border marketplaces and sales volumes.
- **Mean Absolute Percentage Error (MAPE):** MAPE displays model accuracy across various product sales ranges by expressing prediction error as a percentage. Lower MAPE shows that DTS-GNN offers reliable, understandable estimates for international e-commerce platforms.

Table 5: Comparative performance analysis of the CSA-ANN model and the proposed DTS-GNN framework using standard regression metrics

Metrics	CSA-ANN [30]	DTS-GNN [Proposed]
MAE	2.2773	1.8420
RMSE	2.8144	2.2165
NRMSE	0.0711	0.0568
MAPE	13.7211	10.3924
R (Correlation)	0.9031	0.9448

- **R (Correlation Coefficient):** The linear connection between projected and actual sales is measured by R. A higher correlation suggests that DTS-GNN is capable of learning browsing-driven product demand trends across global e-commerce platforms.

Table 5 and Figure 16 (b) display the Comparative performance analysis of the CSA-ANN model and the proposed DTS-GNN method.

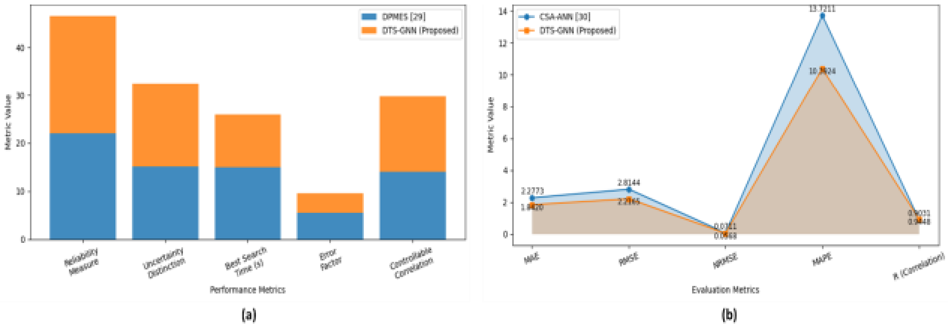

Figure 16: Comparison of CSA-ANN and DTS-GNN across (a) key evaluation metrics and (b) MAE, RMSE, NRMSE, MAPE, and R

The DPMES approach is less successful in noisy, high-dimensional cross-border situations due to its heavy reliance on behavioural dataset size and static correlation mining, which makes it difficult to simulate by quickly changing user-product interactions. Its counting-based forecasting restricts its capacity to adjust by changing market conditions. In the same way, the CSA-ANN model is not strong enough to handle complicated temporal browsing behaviours, which has limited learning capacity for multi-hop relational patterns, and suffers from substantial computational cost during CapSA-based optimization. Although, both methods offer a respectable level of accuracy, neither fully capture the deep structural connections necessary for accurate worldwide sales forecasting. By combining graph-based relational learning with adaptive tangent search optimization, the DTS-GNN framework gets over these restrictions. This allows dynamic weight adjustment, more robust structural modelling, and much better forecasting accuracy in a variety of cross-border scenarios.

The proposed DTS-GNN outperforms existing cross-border e-commerce forecasting models like DPMES and CSA-ANN. DPMES struggles with dynamic user–product interactions due to static correlation mining, while CSA-ANN cannot capture multi-hop relational dependencies, resulting in higher MAE and RMSE. DTS-GNN's superior performance (MAE 1.8420, RMSE 2.2165, R = 0.9448) stems from: (1) GNNs capturing complex, non-Euclidean user–product and temporal relationships, (2) Dynamic Tangent Search optimizing graph weights and hyperparameters efficiently, and (3) PCA-based feature reduction enhancing noise resilience and stability. Its novelty lies in combining tangent-based meta-heuristic optimization with graph representation learning, modeling dynamic relational structures for more accurate and scalable sales forecasting.

The reduction in MAE and RMSE is mainly due to the GNN ability to model multi-hop user–product interactions, which reduces prediction bias compared to traditional ANN models. The improvement in NRMSE and MAPE results from PCA-based dimensionality reduction and Min–Max normalization, which stabilize learning across heterogeneous product categories and regions. The higher correlation (R) indicates that DTS-GNN captures structural relationships between browsing behavior and sales trends more effectively. Additionally, the reduced search time and error factor are achieved through DTS optimization, which prevents local minima and ensures faster convergence.

Practical Implications:

These improvements lead to more accurate demand forecasting, better inventory planning, optimized pricing strategies, reduced stock-out risks, and faster decision-making in dynamic cross-border e-commerce environments. Overall, DTS-GNN enhances both predictive reliability and operational efficiency in real-world global markets.

Applications:

The novelty of the approach lies in the integration of DTS-GNN for cross-border e-commerce sales forecasting. Key innovations include:

- DTS optimizes graph weights and hyperparameters, enhancing model stability and preventing local minima, unlike traditional static optimization methods.
- GNN effectively captures complex user-product relationships and dynamic purchase patterns through multi-hop relational learning.
- PCA reduces dimensionality while preserving important behavioral and transactional patterns, improving efficiency.
- Handles diverse e-commerce data with advanced preprocessing for cleaner, more reliable inputs.
- The DTS-GNN outperforms existing models (e.g., DPMES and CSA-ANN) in key metrics like MAE, RMSE, and MAPE, demonstrating superior predictive accuracy, scalability, and interpretability.

5 Conclusion

The research work applied deep learning techniques, IoT-based data ecosystems, and an adaptive Dynamic Tangent Search-driven Graph Neural Network (DTS-

GNN) towards suggesting a comprehensive intelligent sales prediction system for global e-commerce. The research work comprehensively addressed the critical shortcomings that are largely prevalent in the present prediction models, i.e., the inefficacy of the models in coping with multi-hop dynamic interactions between user-product in a high-dimensional noise environment. The proposed system offers a comprehensive efficient end-to-end prediction mechanism for global e-commerce that includes an efficient data acquisition mechanism, improved pre-processing steps with improved PCA dimensionality reduction, and a superior graph representation learning mechanism. The predictive mechanism's ability to identify superior graph weights for improved convergence speed and avoidance of local minima was comprehensively improved by integrating the DTS optimization technique in the predictive mechanism so that superior structural learning was achieved based on various browsing activities, user-product linkages, and purchasing trends in the long run. Based on the comprehensive experimentation carried out with the superior CSA-ANN mechanism, DPMES mechanism, and DTS-GNN mechanism, it was revealed that critical improvements have been achieved in terms of MAE 1.8420, RMSE 2.2165, NRMSE 0.0568, MAPE 10.3924, R 0.9448, improved reliability 24.6, uncertainty 17.3, search time 10.9 s, error factor 4.1, and correlation 15.8. The results of the experimentation proved the fact that DTS-GNN significantly works well in real-world cross-border e-business scenarios due to the fact that it not only optimizes prediction accuracy but also renders consistent results in various market scenarios. In conclusion, this research offers a superior effective robust comprehensive data-driven mechanism that offers various promising benefits in terms of proactive inventory management, resourceful allocation, and well-informed decision-making towards achieving successful global e-business. This superior DTS-GNN mechanism offers a promising contribution towards designing more intelligent proactive adaptable long-lasting global e-business prediction models that offer superior levels of efficiency.

5.1 Limitations and future scope

The DTS-GNN model shows strong potential for forecasting in cross-border e-commerce, but several limitations must be addressed for real-world applications. The model heavily relies on high-quality, consistent behavioral data, which may not always be available across different e-commerce platforms, especially smaller ones. Additionally, the computational cost associated with the model's complexity may hinder its scalability and real-time processing on large platforms. The model also faces challenges in adapting to dynamic market conditions and new consumer behaviors, necessitating frequent retraining. Moreover, multicultural and multilingual differences in consumer behavior can affect its generalization across diverse regions. Lastly, integrating the model with existing e-commerce infrastructures may encounter technical and data synchronization hurdles.

Future research can focus on improving the model's efficiency for real-time predictions by reducing computational demands. Transfer learning techniques can be explored to enhance the model's adaptability to new markets with limited data. Furthermore, advanced preprocessing methods to handle noisy, incomplete, or multi-modal data could improve its robustness. Developing multilingual models and integrating NLP for cross-cultural insights will be crucial for improving predictions across global markets. Combining DTS-GNN with traditional forecasting methods could provide flexibility in handling both short-term and long-term market trends. Lastly, improving model explainability and adapting it for emerging markets with unique challenges could significantly enhance its applicability in diverse e-commerce scenarios.

Fundoing

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Competing Interests

The author declared no potential conflicts of interest with respect to the research, authorship or publication of this article.

Author contributions

Li. Data curation&Writing

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