



Research on cross-border e-commerce logistics risk early warning and supply chain collaboration based on timing feature analysis

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SUMMARY: *Aiming at the situation of asynchronous events, state jump and complex node linkage in cross-border e-commerce logistics chain, a logistics risk early warning and supply chain collaboration framework based on timing feature analysis was constructed. Based on 138420 order performance records of 16 international transportation routes, 22 attributes such as node stay time, customs clearance interval, transfer frequency, warehouse processing time, distribution offset, transportation capacity status, regional load and abnormal event markers are extracted. Timestamp alignment, piecewise interpolation and min-max normalization are combined to complete data processing. The model consists of three parts: time series feature representation, risk warning and risk linkage. The event window aggregation, time offset calculation, stage position coding, bidirectional time series recognition and collaborative action sequencing are completed in turn. The results show that the proposed method reduces the average response delay to 1.84 s, and the congestion relief rate, performance recovery rate and cross-node consensus reach 21.7%, 90.8% and 92.4% respectively, and maintains a relatively stable warning output under different paths and different risk levels. It provides computational support for risk identification and collaborative scheduling in cross-border e-commerce logistics network and supports subsequent collaborative scheduling.*

KEYWORDS: *Cross-border e-commerce logistics; Temporal feature analysis; Risk early warning; Supply chain collaboration*

1 Introduction

The cross-border e-commerce logistics chain has the characteristics of many nodes, large time differences, strong fluctuations in customs clearance status, long performance paths and decentralized collaborative agents. The whole process of order collection, distribution, customs declaration, trunk transportation and terminal delivery will continuously generate high-frequency event logs, location trajectories and status return data. This kind of data not only contains obvious time sequence relationship, but also contains linkage constraints between warehouse, transportation, customs and distribution. It is difficult to support real-time early warning and collaborative scheduling by relying solely on static rules or manual experience. With the continuous improvement of the informatization degree of logistics platform, the cross-node event flow, order flow and resource flow can be collected and stored in a structured way, which provides a data basis for reconstructing the risk identification and supply chain collaboration mechanism from the perspective of computing.

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Kosasih et al. studied the prediction of hidden links in supply chain, and proposed a method of identifying link relationships by graph neural network, which provided the basis for heterogeneous node association modeling [1]. Wang et al. proposed the framework of smart supply chain driven by digital twin, and illustrated the feasibility of synchronous calculation of physical process and digital mapping [2]. Badakhshan et al. studied inventory and cash management under disturbance scenarios, and used digital twin for supply chain decision analysis under disruption conditions [3]. Zheng et al. proposed a privacy-preserving oriented federated learning risk prediction method, which verified the application value of cross-agent collaborative modeling in supply chain scenarios [4]. Bodendorf et al. studied supply disruption analysis and prediction and proposed a hybrid method combining causal inference with deep learning [5].

Aljohani studied real-time supply chain risk mitigation and pointed out the role of predictive analysis and machine learning in agile response [6]. Sani et al. proposed a supply chain risk prediction model based on Bayesian optimization LightGBM, which improved the stability of risk classification [7]. Kolley et al. studied berth scheduling under the support of vessel arrival time prediction, indicating that time series prediction results can directly affect resource allocation [8]. El Mekkaoui et al. proposed a deep learning model for the estimated arrival time of ships in bulk ports, indicating that time estimation in complex transportation scenarios can achieve higher accuracy through deep networks [9]. Khedr systematically combed the application of deep learning and machine learning in supply chain management, and pointed out that multi-source data fusion, sequence modeling and intelligent decision-making are important directions for the evolution of current methods [10].

Existing research has covered link identification, time of arrival prediction, risk classification and digital mapping, but the integrated research on time series feature expression, risk linkage recognition and collaborative response calculation in cross-border e-commerce logistics scenarios is still insufficient. The risk in cross-border business is not a single point event, but a dynamic propagation process driven by customs declaration delay, warehouse congestion, transport capacity switching, air route fluctuation and regional performance imbalance. If the risk status can not be represented continuously at the time sequence level and the node response can not be reasoned synchronously at the coordination level, it is difficult to convert the early warning results into executable scheduling actions.

Based on the above research background and technical progress, this paper takes the order flow, transportation flow, node job flow and state back transmission flow in cross-border e-commerce logistics as the unified analysis object, and focuses on three levels: time series feature representation, risk early warning calculation and collaborative linkage reasoning. In the method design, the computational characteristics of asynchronous arrival, state jump, node coupling and risk propagation in the logistics event sequence are focused on, and the order performance status, transportation phase change, warehouse allocation resource load and abnormal disturbance information are incorporated into the unified modeling process, so as to form a risk early warning and supply chain collaborative analysis framework for cross-border e-commerce scene. The following contents of this paper will discuss the related research progress, model construction method, time series feature representation process, risk early warning implementation mechanism and collaborative linkage results in turn, so as to provide a continuous technical analysis basis for risk identification and collaborative calculation in cross-border logistics network.

2 Literature Review

The computational research of cross-border e-commerce logistics risk early warning and supply chain collaboration needs to simultaneously process three types of information: multi-node time series events, heterogeneous state return and cross-agent collaborative control. Existing literature has explored from the directions of digital twin, deep learning, graph neural network and data-driven optimization, and gradually incorporated state perception, risk identification, time prediction and resource linkage in logistics networks into a unified computing framework. The progress of related research shows that the focus of modeling in cross-border logistics scenarios has shifted from static business analysis to continuous representation oriented to event flow, risk estimation oriented to disturbance propagation, and collaborative reasoning oriented to network response, which provides a reference technical basis for constructing a risk early warning and supply chain collaboration method fused with time series feature analysis.

Ashraf et al. studied the disruption detection in cognitive digital supply chain twin, and proposed a disturbance recognition mechanism driven by hybrid deep learning to make the supply chain state mapping transform from static monitoring to dynamic calculation [11]. Ye studied cross-border e-commerce logistics and supply chain network optimization, and proposed the idea of network structure reorganization for cross-border scenarios, indicating that there is a tight coupling relationship between logistics link configuration and computing scheduling [12]. Ozarik et al. studied data-driven terminal distribution optimization and proposed a distribution decision-making method supported by machine learning, which enhanced the utilization ability of real-time data in the logistics process [13]. Camur et al. studied the prediction of product availability date under disturbance conditions, and proposed a method to enhance supply chain resilience based on machine learning, linking time series prediction with performance recovery [14]. Gabellini et al. studied delivery delay risk prediction based on macroeconomic indicators, and proposed a deep learning delay risk estimation model to expand the input boundary of risk calculation [15].

Rokoss et al. studied the determination of delivery time in small batch production enterprises, proposed a delivery cycle calculation method supported by machine learning, and verified the time inference ability in complex manufacturing logistics chain [16]. Pasupuleti et al. studied the machine learning optimization technology in logistics and inventory management, and proposed a collaborative computing path that takes into account both agility and sustainability, so that transportation, inventory and response control can be connected under a unified framework [17]. Niu et al. studied supply chain demand forecasting based on graph convolutional network, and proposed a method to express node association and demand conduction by using graph structure, which provided a new implementation way for cross-node temporal dependence modeling [18]. Peng et al. studied the railway cold chain freight demand prediction and proposed the GraphARMA-GRU model, which integrated graph relationship modeling and gated temporal learning to enhance the dynamic prediction ability in complex networks [19]. Abdi and Amrit studied the prediction of ship arrival time and proposed a time estimation method based on fusion deep learning, illustrating the value of multi-source timing features in transportation chain calculation [20]. The above studies have expanded the technical boundaries of logistics intelligent analysis from the perspectives of disruption detection, network optimization, demand forecasting, delay estimation and arrival time calculation, respectively. However, most of them focus on a single task in the context of cross-border e-commerce, and the linkage modeling coverage of risk early warning and supply chain collaboration is still insufficient.

To facilitate the comparison of the differences in data structures, key indicators and method adaptation of existing studies, Table 1 summarizes the related work. It can be seen from the table that existing methods have made significant progress in prediction accuracy and task adaptability, but different studies pay different attention to the depth of time series expression, cross-node dependencies and linkage decision output, which also determines the transfer scope of relevant results in cross-border e-commerce logistics risk early warning scenarios.

Table 1: Summary of related studies

Reference	Research Object	Main Method	Implications for This Study
[11]	Disruption detection in digital supply chain twins	Hybrid deep learning	Suitable for dynamic identification of logistics risk states
[12]	Cross-border e-commerce logistics network optimization	Network reconfiguration and computational scheduling	Helpful for collaborative structure modeling in supply chains
[13]	Last-mile delivery optimization	Data-driven machine learning	Strengthens the real-time utilization of logistics events
[14]	Product availability date prediction under disruptions	Machine learning-based resilience prediction	Supports fulfillment recovery computation after risk warning
[15]	Delivery delay risk estimation	Macro indicators combined with deep learning	Expands the input feature boundary for delay risk
[16]	Delivery time determination	Machine learning-based cycle calculation	Suitable for constructing time-related risk discrimination variables
[17]	Collaborative optimization of logistics and inventory	Machine learning optimization techniques	Indicates that the linkage between transportation and inventory can be computationally modeled
[18]	Supply chain demand forecasting	Graph convolutional network	Suitable for representing node associations and propagation relationships
[19]	Cold-chain freight demand forecasting	GraphARMA-GRU	Suitable for integrated modeling of graph structures and temporal features
[20]	Ship arrival time prediction	Integrated deep learning	Indicates that multi-source temporal features are effective for transportation computation

A comprehensive review of the above research shows that the existing results have formed a clear accumulation of technologies in supply chain disruption detection, cross-border logistics network optimization, delivery timeliness prediction, demand modeling and collaborative scheduling. Methods such as deep learning, graph neural network and digital twin have gradually entered the logistics intelligent computing scene. Existing research has provided reference modeling ideas for the state perception and risk identification of

cross-border e-commerce logistics. However, most of the different methods focus on a single task, and time series feature representation, risk early warning calculation and supply chain collaboration are often scattered in different research frameworks, which have not yet formed a continuous connection in the unified calculation process. For cross-border e-commerce logistics scenarios, order performance status, transportation node changes, warehouse distribution load fluctuations and abnormal disturbance propagation have obvious temporal coupling characteristics, and it is difficult to directly support cross-node collaborative response by only relying on local prediction results.

3 Research Methods

3.1 Logistics risk early warning and supply chain collaboration model construction

The cross-border e-commerce logistics chain contains multiple stages such as order creation, warehouse processing, trunk transfer, customs clearance and release, regional distribution and terminal delivery. There are obvious differences in time granularity, data density and business meaning of state records generated by different stages. If the state is judged only by a single node or a single moment, the early warning results are easy to stay at the local level, and it is difficult to continue to be transmitted to the collaborative execution links such as warehouse scheduling, transportation capacity allocation and replenishment adjustment. In order to make risk identification and supply chain collaboration form a continuous calculation process, this paper constructs a logistics risk early warning and supply chain collaboration model, which maps the order status flow, transportation status flow, node job flow and abnormal disturbance flow into the same computing framework, and completes the unified state coding, risk propagation calculation, collaborative relationship reasoning and linkage result output in turn. The overall model adopts the hierarchical structure of "input mapping-state aggregation-risk discrimination-collaborative decision", so that the discrete events in cross-border logistics can be transformed into continuous risk control signals.

In order to keep order performance deviation, transportation phase change, node load intensity and abnormal disturbance information synchronously in the same computational space, this paper first defines a unified input state vector, so that subsequent risk propagation and collaborative reasoning can be carried out in a consistent data structure, and its expression is as follows:

$$s_t = \Theta_1[o_t||l_t||n_t||e_t] + b_1 \quad (1)$$

where s_t denotes the integrated state vector at time t ; o_t represents the order performance attribute vector; l_t represents logistics time-effectiveness offset vector; n_t represents the node load and resource occupancy vector; e_t represents the abnormal event vector; Θ_1 and b_1 denote the mapping parameter and the bias term, respectively. The function of equation (1) is to compress the multi-source states with different sources, scales, and semantics into a unified representation space, avoiding the accumulation of bias caused by inconsistent input formats in the risk calculation stage.

After the unified state is formed, the model needs to describe the diffusion relationship of risk in the node network. The delay in cross-border logistics does not stay at a single node, and the processing congestion in the warehouse, the fluctuation of the airline route and the change of the customs clearance rhythm will be transmitted along the radial direction of the subsequent nodes. Therefore, this paper adopts the node aggregation mechanism with time

recurrence ability to generate the node hidden state, and its expression is as follows:

$$q_v^{(t)} = \text{GRU} \left(\sum_{u \in \Omega(v)} \alpha_{u,v}^{(t)} \Theta_2 s_u^{(t)} + \beta_v s_v^{(t)}, q_v^{(t-1)} \right) \quad (2)$$

Here, $q_v^{(t)}$ represents the sequential aggregation state of node v at time t . Let $\Omega(v)$ denote the set of nodes connected to node v ; $\alpha_{u,v}^{(t)}$ represents the propagation weight between nodes; β_v represents the local state contribution coefficient; Let Θ_2 denote the projection parameters. Equation (2) incorporates the state input of neighboring nodes and the node's own state into the recurrence unit, so that the model can perceive the upstream disturbance input and local load change at the same time, so as to describe the risk diffusion process more accurately.

After the node status is continuously updated, the model also needs to establish a correspondence between the risk status and the coordination requirements. The backlog intensity of the warehouse node, the delay degree of the transportation node and the tension level of the replenishment node are not completely consistent, and the synergy relationship cannot be given by static rules. In order to generate the synergy strength matching the current risk state, this paper defines the linkage weight between nodes as follows:

$$c_{u,v}^{(t)} = \frac{\exp\left((r_u^{(t)})^\top k_v^{(t)} / \sqrt{d}\right)}{\sum_{j \in \Omega(u)} \exp\left((r_u^{(t)})^\top k_j^{(t)} / \sqrt{d}\right)} \quad (3)$$

where $c_{u,v}^{(t)}$ represents the collaborative linkage weight of node u to node v . $r_u^{(t)}$ represents the risk query vector of node u ; $k_v^{(t)}$ represents the cooperative bond vector of node v ; d denotes the vector dimension. Formula (3) uses the normalized attention calculation method to form a dynamic matching relationship between risk propagation and collaborative response, and can automatically adjust the linkage priority according to the real-time state.

In order to transform the risk status, collaboration relationship and execution constraints into the final output results, the model sets up a multi-task output layer at the end, and gives the warning level, linkage priority and scheduling suggestions, whose expression is as follows:

$$y_t = \text{Softmax}(\Pi_1 [r_t \| c_t \| g_t] + b_2) \quad (4)$$

where y_t represents the model output at time t ; r_t represents the global risk summary vector; c_t represents collaborative relationship vector; g_t represents the fusion vector of resource constraint and performance goal. Π_1 and b_2 denote the output layer parameters and the bias term, respectively. Equation (4) directly connects the risk warning results to the collaborative execution end, so that the model output no longer stays at the classification level, but can continue to support resource scheduling and response sequencing.

In order to more clearly show the internal composition of the logistics risk early warning and supply chain collaboration model, Fig. 1 shows the overall structure process from multi-source input to linkage output. In the diagram, the order flow, transportation flow, node state flow and abnormal event flow are organized under the same time index, and then mapped to the state encoding, risk propagation, collaborative reasoning and output decision modules in turn.

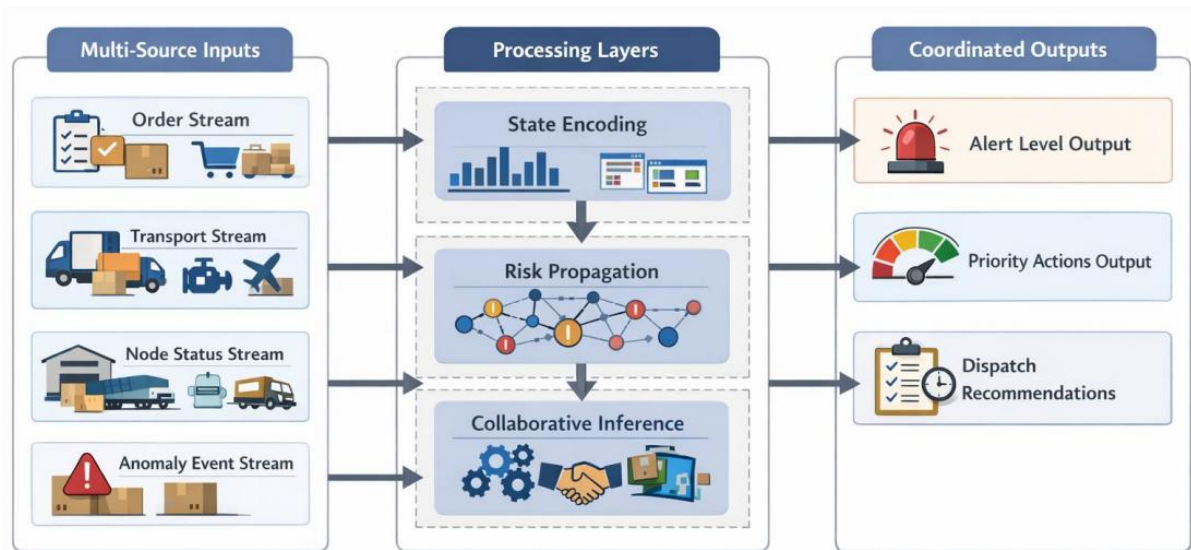


Figure 1: Structural diagram of logistics risk early warning and supply chain collaboration model

In Fig. 1, the left side is the multi-source input, including order status, logistics status, node load and abnormal disturbance information. The middle part is unified state mapping layer, time series aggregation layer and collaborative relationship calculation layer. On the right side are the output of warning level, linkage priority and scheduling suggestion. The structure makes risk identification, node association and collaborative control form a continuous calculation chain, which is conducive to the subsequent feature representation, risk discrimination and linkage execution in the same framework to complete the training and verification.

Through this model construction process, the order status, transportation status, node load and abnormal disturbance in cross-border e-commerce logistics are incorporated into the same computational framework, and the risk propagation and collaboration relationship is continuously expressed in the unified network. In this model, early warning identification, node association and linkage output are processed in the same reasoning chain, which enhances the correspondence between risk state and collaborative behavior, and makes multi-source logistics data have clearer structural consistency and engineering availability at the calculation level.

3.2 Temporal feature representation method of cross-border e-commerce logistics

Cross-border e-commerce logistics events have significant asynchronous arrival characteristics. The creation, outbound, handover, customs declaration, release, arrival and receipt of orders are not generated under a uniform sampling frequency. Some nodes return sparse information, while some nodes return dense information. If the original event sequence is directly fed into the risk model, it is easy to cause the instability of state expression and the confusion of phase semantics. In order to ensure that the state changes under different paths, different regions and different nodes can enter a unified comparison space, this paper designs a time series feature representation method for cross-border e-commerce logistics, which completes event window aggregation, time offset calculation, stage position coding, local time series convolution and gated feature update in sequence. The original event stream is transformed into a unified temporal representation that is trainable, aligned and comparable.

In order to preserve the arrival density of events and the order relationship between adjacent events in the local time range, this paper reorganizes the original logistics event stream by sliding window aggregation, so that the discrete scanning records can form a continuous local representation, and its expression is as follows:

$$z_t = \sum_{\tau=t-l+1}^t \eta_{\tau,t} x_{\tau} \quad (5)$$

Here, z_t denotes the window aggregation representation at time t . l is the window length; Let $\eta_{\tau,t}$ denote the event weights within the window; Let x_{τ} denote the original event vector at time τ . The function of formula (5) is to organize the sparse, discrete event stream with different time granularity into local continuous segments, which can provide stable input for subsequent offset calculation and stage coding.

After the formation of the local window, it is also necessary to judge the degree of offset of the event occurrence rhythm with respect to the plan performance rhythm. Because the planned arrival time, transit time and customs clearance rhythm of different orders are not the same, it is not beneficial to use absolute time difference directly for comparison between different samples. Therefore, relative time offset is defined as follows in this paper:

$$\delta_t = \frac{T_t - \hat{T}_t}{\max(\hat{T}_t, \varepsilon)} \quad (6)$$

Here, δ_t denotes the relative time offset at time t ; T_t is the time when the actual event occurs. \hat{T}_t denotes the time of the planned event; Let ε denote the stability constant. Formula (6) can uniformly normalize the time deviations in different performance paths, so that delay, advance and rhythm anomaly can be characterized under the same scale.

In addition to the temporal order, logistics events also have explicit phase semantics. Even if they are close in time and position, the business meanings of collection, delivery, trunk transportation, customs clearance and delivery are obviously different. In order to make the model aware of time location and performance phase simultaneously, this paper introduces phase location coding, which is expressed as follows.

$$p_{t,2i} = \sin\left(\frac{g_t}{10000^{2i/d}}\right), \quad p_{t,2i+1} = \cos\left(\frac{g_t}{10000^{2i/d}}\right) \quad (7)$$

Here, $p_{t,2i}$ and $p_{t,2i+1}$ represent the even and odd dimensions of positional encoding, respectively. g_t denotes the event phase index. d denotes the feature dimension. Formula (7) makes the events in different stages retain a clear distinction in the same vector space, which can reduce the recognition bias caused by phase semantic aliasing.

After obtaining window aggregations and stage locations, the model needs to continue to refine local timing patterns. Short-term congestion, continuous delay, node stagnation and scan missing in cross-border logistics often show local fluctuations. Therefore, this paper adopts one-dimensional time convolution to scan the local dynamics, and its expression is as follows:

$$m_t^{(k)} = \phi\left(\sum_{j=0}^{h-1} \theta_j^{(k)} [z_{t-j} \| p_{t-j} \| \delta_{t-j}] + b_k\right) \quad (8)$$

where $m_t^{(k)}$ represents the response of the k kernel at time t ; h represents the length of the convolution kernel; Let $\theta_j^{(k)}$ denote the convolution parameters; p_{t-j} denotes the positional encoding; b_k denotes the bias term; Let $\phi(\cdot)$ denote the activation function. Equation (8) is used to extract highly sensitive patterns in the local time range, so that the model can remain sensitive enough to short-term anomaly accumulation.

After the local convolutional response is formed, it is necessary to further construct a smoother unified temporal representation. There are occasional noise and irregular sampling in the original event stream, and the feature sequence is easy to jump if the convolution result is directly used. To this end, this paper fuses the current local response and historical state through the gated update mechanism, whose expression is as follows:

$$u_t = \lambda_t \odot u_{t-1} + (1 - \lambda_t) \odot m_t \quad (9)$$

where u_t represents the updated unified temporal representation; Let λ_t denote the gating weight; \odot for element-wise multiplication; m_t denotes the convolution response vector. Formula (9) can suppress the violent fluctuations caused by occasional noise, while retaining the influence of local anomalies on subsequent risk identification, so that the time series representation has both stability and sensitivity.

In order to more intuitively illustrate how the original event stream can be transformed into a trainable unified representation, Fig. 2 shows the process of cross-border e-commerce logistics temporal feature representation. The figure shows the five calculation links of window segmentation, time offset calculation, stage position coding, local convolution extraction and gated update in turn, so that the input source of the subsequent early warning model can directly correspond to the content of this section.

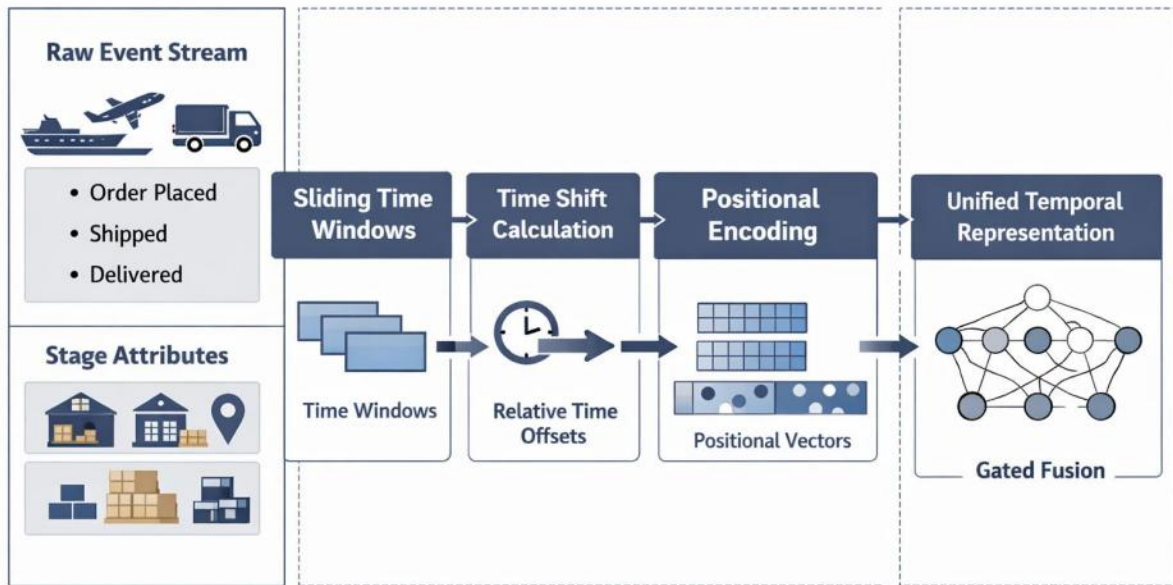


Figure 2: Flow chart of temporal feature representation for cross-border e-commerce logistics

In Fig. 2, the left side shows the original logistics event flow and stage attribute input, the middle part shows the sliding window aggregation, relative time offset calculation, position coding mapping and local time convolution module, and the right side shows the unified

timing feature representation after gated update. This process enables logistics records under different paths, different stages and different node densities to form continuous features in a unified space, and provides stable input sequences with stage semantics for the risk warning module.

Through this temporal feature representation process, the original logistics events are transformed from discrete log form into a unified vector sequence with time order, phase semantics, local fluctuation and performance offset information. This representation not only retains the sensitivity of short-term abnormal changes to risk formation, but also maintains the continuous state of long-link orders in multi-stage operation, so that the complex event flow in cross-border e-commerce logistics can obtain stable, detailed and comparable expression results in the same feature space.

3.3 Logistics risk early warning method integrating time series features

After the unified time series representation is formed, the model needs to further judge the risk intensity and warning level at each moment. The risk in cross-border logistics is not only manifested by the increase of final delay value, but also continuously accumulated in the form of customs clearance rhythm imbalance, transit node stagnation, regional load lifting and terminal receipt deviation expansion. If the risk calculation only depends on the feature vector at a single time, it is difficult to capture the dynamic process of anomaly diffusion from the local stage to the whole path. To this end, this paper designs a logistics risk early warning method combining time series features. On the basis of unified representation, bidirectional time series coding, key segment focusing, risk summary generation and hierarchical early warning output are completed in turn, so that the model can maintain the ability to identify local anomalies and global trends at the same time.

In order to completely preserve the forward and backward dependence of the event sequence, this paper introduces a bidirectional encoding mechanism after unifying the time series representation, which absorbs the context information of the historical state and the subsequent state at each time position. The expression is as follows:

$$b_t = \tanh(\Lambda_1 \vec{u}_t + \Lambda_2 \bar{u}_t + b_3) \quad (10)$$

Here, b_t represents the bidirectional fusion state at time t . \vec{u}_t represents the forward encoding result. \bar{u}_t represents the backward encoding result; Λ_1 , Λ_2 , and b_3 denote the mapping parameters. Equation (10) enables the model to identify risk turning points and abnormal accumulation paragraphs more accurately by simultaneously utilizing the anteroposterior timing information.

Not all temporal locations contribute equally to the warning results. The concentrated section of customs clearance delay, the route switching section and the stagnation section in the warehouse usually have a greater impact on the risk level. Therefore, this paper adopts the time attention mechanism to strengthen the highly sensitive segment, and the dynamic risk score expression is as follows:

$$r_t = \sigma(a^T \tanh(\Gamma_1 b_t + c_1) + \psi^T d_t) \quad (11)$$

Here, r_t represents the risk intensity score at time t ; a and ψ denote the risk projection vector; Γ_1 and c_1 denote the mapping parameters; d_t represents the dynamic offset feature at the current moment. Equation (11) encodes the bidirectional fusion state and the dynamic offset information into the risk intensity jointly, so that the risk score can reflect the time context and the abnormal amplitude of the current stage at the same time.

In order to further transform the continuous risk score into an executable warning level, the risk intensity, bidirectional state and key offset information are jointly input into the hierarchical output layer to generate a multi-level warning probability distribution, whose expression is as follows:

$$\hat{y}_t = \text{Softmax}(\Pi_2[r_t||b_t||d_t] + b_4) \quad (12)$$

where \hat{y}_t represents the probability of warning level at time t ; Let Π_2 and b_4 denote the hierarchical output layer parameters; d_t represents the dynamic offset and disturbance characteristics. Formula (12) maps the continuous score and context state into discrete warning levels, so that the subsequent collaborative linkage module can generate action plans based on clear grading results.

In order to ensure that the model still has a relatively stable recognition ability under unbalanced risk samples, and suppress violent oscillations between temporal adjacent positions, this paper uses a joint objective function containing classification loss and smoothness constraints for training, and its expression is as follows:

$$\mathcal{L} = \mathcal{L}_{ce} + \lambda_1 \mathcal{L}_{focal} + \lambda_2 \sum_{t=2}^T |r_t - r_{t-1}| \quad (13)$$

Here \mathcal{L}_{ce} represents the cross-entropy loss; \mathcal{L}_{focal} denotes the focal loss; λ_1 and λ_2 represent the balance coefficients; $|r_t - r_{t-1}|$ represents the risk score difference at adjacent moments. Formula (13) not only strengthens the identification ability of a few risk samples, but also restricts the continuity of the early warning sequence, so that the model output is more in line with the time characteristics of gradual accumulation of risks in the real logistics scenario.

Through this early warning calculation process, the time series characteristics are further transformed from the state description into the risk results with the ability to distinguish between grades and the form of probability output. The key segments, cumulative intensity and fluctuation trend in the process of risk formation are also more centrally described. This method enhances the ability of the model to identify continuous anomalies, stage offset and node disturbance, so that the risk output has stronger discriminant stability and result interpretation while maintaining time sensitivity.

3.4 Risk linkage method for supply chain collaboration

If the risk early warning results stay at the recognition level, the model can only complete the state judgment, and cannot continue to support the action coordination between storage nodes, transportation nodes and replenishment nodes. The abnormal state in cross-border e-commerce logistics will continue to spread along the supply chain, the detention in the warehouse will cause the deviation of the transshipment schedule, the fluctuation of the trunk line will affect the end distribution order, and the shortage of inventory will reverse change the replenishment priority. Therefore, the risk linkage method for supply chain collaboration needs to transform the early warning results into collaborative driving coefficient, action benefit and execution probability, so that the scheduling behaviors of different nodes can realize linkage update around the same risk state. Based on this idea, this paper continues to build the linkage decision layer after the risk warning output, and completes the calculation mapping from risk level to collaborative action.

In order to quantify the driving degree of risk state on node linkage, this paper first defines the risk-driving coefficient of nodes, and puts the risk level, node importance and resource tension into the same calculation formula, so that the linkage requirements of different nodes can be uniformly compared. The expression is as follows:

$$\eta_v^{(t)} = \rho_1 \hat{y}_v^{(t)} + \rho_2 \kappa_v^{(t)} + \rho_3 \mu_v^{(t)} \quad (14)$$

where $\eta_v^{(t)}$ represents the risk-driven coefficient of node v at time t . $\hat{y}_v^{(t)}$ represents the node warning output; $\kappa_v^{(t)}$ represents the importance of node service. $\mu_v^{(t)}$ represents the node resource tension. Let ρ_1 to ρ_3 denote the combination coefficients. Equation (14) enables the early warning results to continue to enter the collaborative layer and form the quantitative driving force for action decision making.

After the driving coefficient is formed, the model needs to evaluate the payoff level of different cooperative actions in the current state. The impact of warehouse switching, capacity reallocation, path substitution and replantation priority adjustment on performance efficiency is not consistent. Therefore, this paper introduces an action benefit function to jointly model the risk reduction range, execution cost and performance gain, whose expression is as follows:

$$\psi_a^{(t)} = \eta^{(t)} \omega_a - \lambda \text{Cost}_a^{(t)} + \xi \text{Gain}_a^{(t)} - v \text{Delay}_a^{(t)} \quad (15)$$

Here, $\psi_a^{(t)}$ represents the linkage payoff of action a at time t . ω_a denotes the action adaptation weight; $\text{Cost}_a^{(t)}$ is the execution cost; $\text{Gain}_a^{(t)}$ is the performance gain; $\text{Delay}_a^{(t)}$ is the additional delay required for the action to execute. Let λ, ξ, v denote the equilibrium parameters. Equation (15) makes the linkage decision not only pursue the decrease of risk score, but form a more stable trade-off relationship among the performance goal, resource consumption and action cost.

After the action payoff is obtained, the model needs to output the final collaborative action priority. In order to form a comparable execution probability for multiple candidate actions at the same time, this paper uses constraint normalization to generate the action distribution, whose expression is as follows:

$$\pi_a^{(t)} = \frac{\exp(\psi_a^{(t)})}{\sum_{j=1}^A \exp(\psi_j^{(t)})} \quad (16)$$

where $\pi_a^{(t)}$ is the execution probability of action a at time t . A denotes the total number of candidate actions. Formula (16) makes different nodes and different actions be sorted under a unified scale, so as to provide a direct scheduling basis for the collaborative execution layer.

In order to clearly show the function mode of risk linkage output in the collaborative layer of the supply chain, Table 2 summarizes the trigger basis, adjustment scope and execution target of various collaborative actions. This table corresponds to the drive calculation, payoff ranking, and action selection processes in the linkage method, and helps to illustrate how the model output is transformed into concrete collaborative control results.

Table 2: Mapping relationship of risk linkage actions

Coordinated Action	Main Driving Source	Adjustment Object	Output Target
Warehouse switching	Regional congestion, in-warehouse backlog	Warehousing node	Reduce local fulfillment pressure
Transport capacity reallocation	Trunk-line fluctuation, load imbalance	Transportation node	Improve route passage efficiency
Route substitution	Customs clearance delay, port congestion	Routing node	Shorten the range of abnormal propagation
Replenishment priority adjustment	Demand shift, inventory shortage	Replenishment node	Stabilize the subsequent fulfillment rhythm
Order resequencing	Last-mile delay, resource conflict	Fulfillment queue	Control the spillover of high-risk orders

Through this risk linkage method, the early warning results are further transformed from pure grade output into comparable, orderable and executable collaborative action signals, and the response order among storage, transportation, replying and performance nodes is also included in the unified decision-making process. The linkage output formed in this way can continue to transfer the abnormal state in cross-border e-commerce logistics to supply chain collaborative control information, so that the front-end warning and back-end scheduling are continuous in the same computing chain.

4 Results and discussion

4.1 Experimental Setup

This section focuses on data configuration, training environment, parameter setting and evaluation method. The experiment uses cross-border e-commerce logistics business data, which contains a total of 138,420 order performance records covering 16 international transportation paths and 22 temporal, spatial and operational attributes. The attribute content includes node stay time, customs clearance interval, transshipment frequency, warehouse processing time, distribution offset, capacity status, regional load and abnormal event marker. In order to ensure the consistency of the model input, the original data are aligned with timestamps, and then the missing items are completed by piecewise interpolation, and the min-max normalization is used to process continuous variables.

The samples were divided into training set, validation set and test set according to 7 : 1.5 : 1.5. At the same time, stratified sampling was performed according to the risk level distribution to ensure that the proportion of each subset in the warning category and path type was consistent. The model is implemented in Python 3.11 and PyTorch 2.2 environment, running on Intel Xeon Gold 6430 processor, 128 GB memory and NVIDIA RTX 4090 graphics card. The width of the convolution kernel of the time series representation module is set to 3 and 5, the number of convolution channels is set to 64 and 128, the dimension of the bidirectional sequence coding unit is set to 128, the hidden dimension of the collaborative linkage layer is set to 96, and the dropout rate is set to 0.3.

In the training phase, AdamW optimizer was used, the initial learning rate was 0.0003, the batch size was 64, and the maximum number of training rounds was 120. If the validation set was not improved for 12 consecutive rounds, it was stopped early. The loss function is composed of cross-entropy, focal loss and smoothness constraint. The comparison models

include LSTM, GRU, CNN-LSTM, BiGRU, and graph convolutional timing model. The evaluation metrics were Accuracy, Precision, Recall, F1-Score, ROC-AUC, MAE, RMSE, and cooperative response delay. To ensure repeatability, the random seed was uniformly fixed to 42 before training, and five-fold cross validation was performed for all experiments. The above Settings make model training, risk identification and linkage evaluation maintain a unified calculation aperture, and also provide a stable experimental basis for subsequent results comparison.

4.2 Analysis results of timing characteristics of cross-border e-commerce logistics

This section mainly investigates the compression ability, stage discrimination ability and abnormal sensitivity of the temporal feature representation module to the cross-border e-commerce logistics event flow. The test set contains 20763 order performance samples, covering 16 international transportation routes and 22 temporal, spatial and operational attributes. After window aggregation, time offset coding, phase position mapping and gating update, the original event forms a unified temporal representation. The results show that the processed features are significantly better than the original event features in terms of stage boundary clarity, inter-class separation and cross-path consistency, indicating that the method can transform discrete logistics logs into computational representations with continuity, structure and comparability.

In order to observe the characteristic activity of different performance stages on the timeline, Fig. 3 shows the thermal distribution of critical incident response for 16 international transportation routes. The results show that the characteristics of customs clearance waiting, secondary distribution and terminal delivery have the strongest response. The average response value of the Asia-Europe route in the customs clearance stage reaches 0.81, and the North American route in the regional distribution stage reaches 0.77, which are significantly higher than the average level of 0.42 of the common transportation nodes. The response intensity of the delay samples in customs clearance interval and node residence time is higher than that of the on-time samples, and the high response area is mainly concentrated in the period of path switching and regional switching, indicating that the unified timing representation has been able to integrate node switching, rhythm deviation and local congestion into the continuous representation, and form a strong response to the high-risk stage.

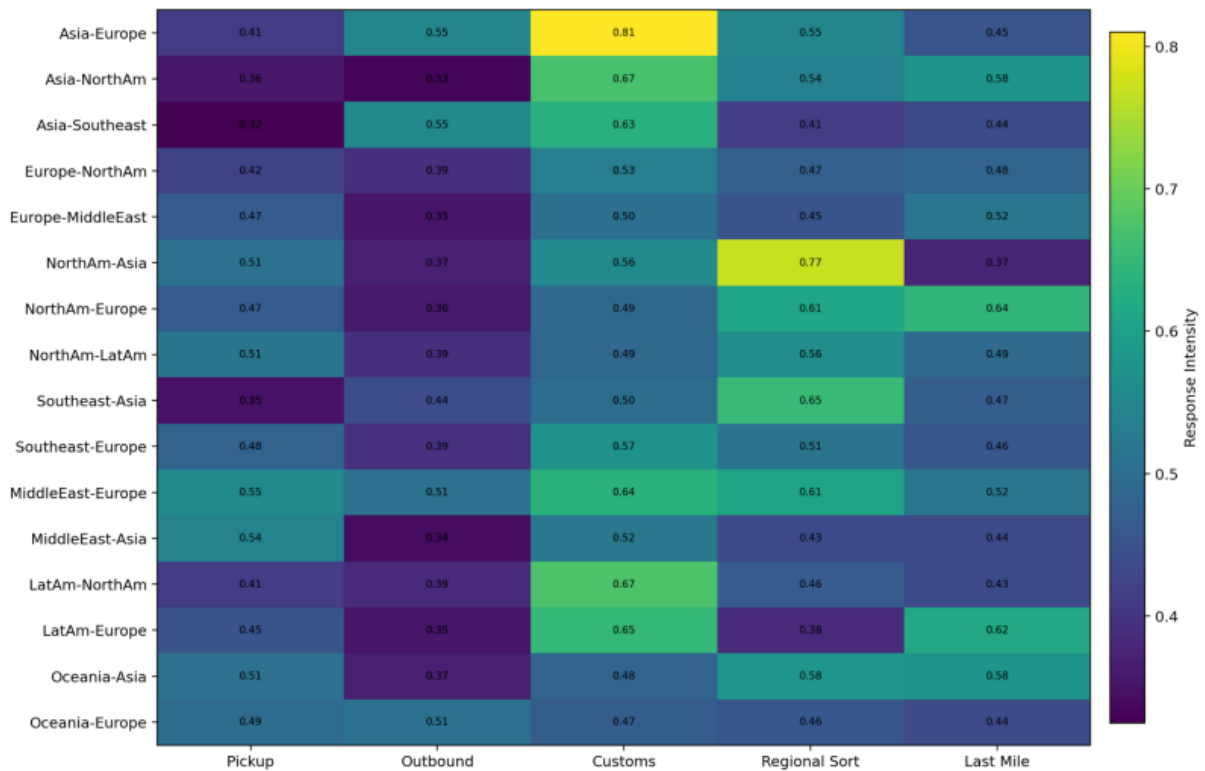


Figure 3: Heat map of response of key timing features

To test the feature separability after the unified representation, Fig. 4 shows the 2-D reduced projection results of the gated updated features. A clear boundary was formed between the four state clusters. The normal performance samples were concentrated in the low deviation area, the potential risk samples were located in the transition zone, and the dominant risk samples and linkage trigger samples were contracted to the high-density area. Compared with unencoded features, the average distance between classes is increased from 1.36 to 2.41, the Davies-Bouldin index is decreased from 0.92 to 0.47, and the contour coefficient is increased from 0.41 to 0.68, which indicates that positional encoding and gating update jointly enhance the separability between different stages of states. It also reduces the case that abnormal samples are covered by normal samples. The dimension reduction results also show that the cross-path samples do not appear obvious fracture, but form a stable hierarchy in a unified space, which is conducive to the subsequent risk score expansion at the same scale.

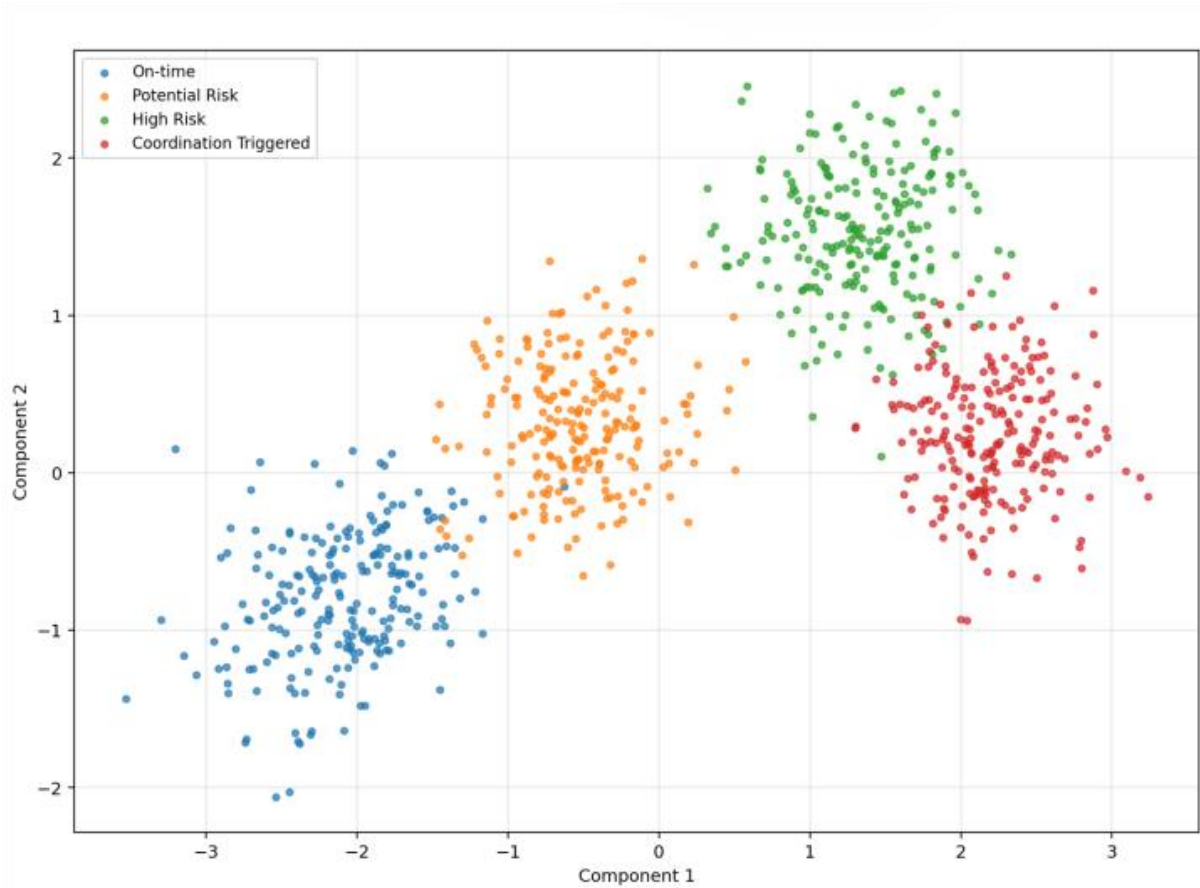


Figure 4: Projection of dimensionality reduction of gated timing features

Summarizing the results of this section, it can be seen that the unified temporal representation module has compressed the time order, phase semantics, local congestion and delay offset of the original logistics events into a stable vector structure. The time series feature representation method preserves this continuity better, and also provides a clearer, more detailed and trainable input basis for subsequent risk warning.

4.3 Logistics risk early warning results integrating timing features

Under the condition of uniform time series feature input, the risk early warning module further undertakes the identification task of samples from different paths, different stages and different risk levels. The risk status in cross-border e-commerce logistics does not only show an abnormal increase of a single node, but gradually accumulates along the performance chain, and forms continuous fluctuations in key stages such as customs clearance, transshipment, distribution and terminal delivery. Based on this feature, this paper analyzes the early warning results from three aspects: the overall discrimination ability, the level discrimination effect and the score continuity, so as to verify the recognition stability and output reliability of the risk early warning method fused with timing features in complex logistics scenarios.

To analyze the recognition balance between different risk levels, Fig. 5 shows the test set confusion matrix results. The recognition rate of normal samples was 95.6%, the recognition rate of mild risk samples was 92.1%, the recognition rate of moderate risk samples was 93.8%, and the recognition rate of dominant risk samples was 94.9%. The main confusions were between mild risk and moderate risk, accounting for 47.3% of the total errors, while the cross misjudgment between dominant risk samples and normal samples was very few, accounting

for only 6.8% of the total errors. This distribution shows that the model has a strong ability to distinguish high-risk cumulative states, and maintains a good recognition balance for neighboring risk levels. The main diagonal area of the matrix is dense and stably distributed, and there is no skew phenomenon dominated by a single path, which indicates that the early warning model has good generalization in different regions and different performance rhythms.

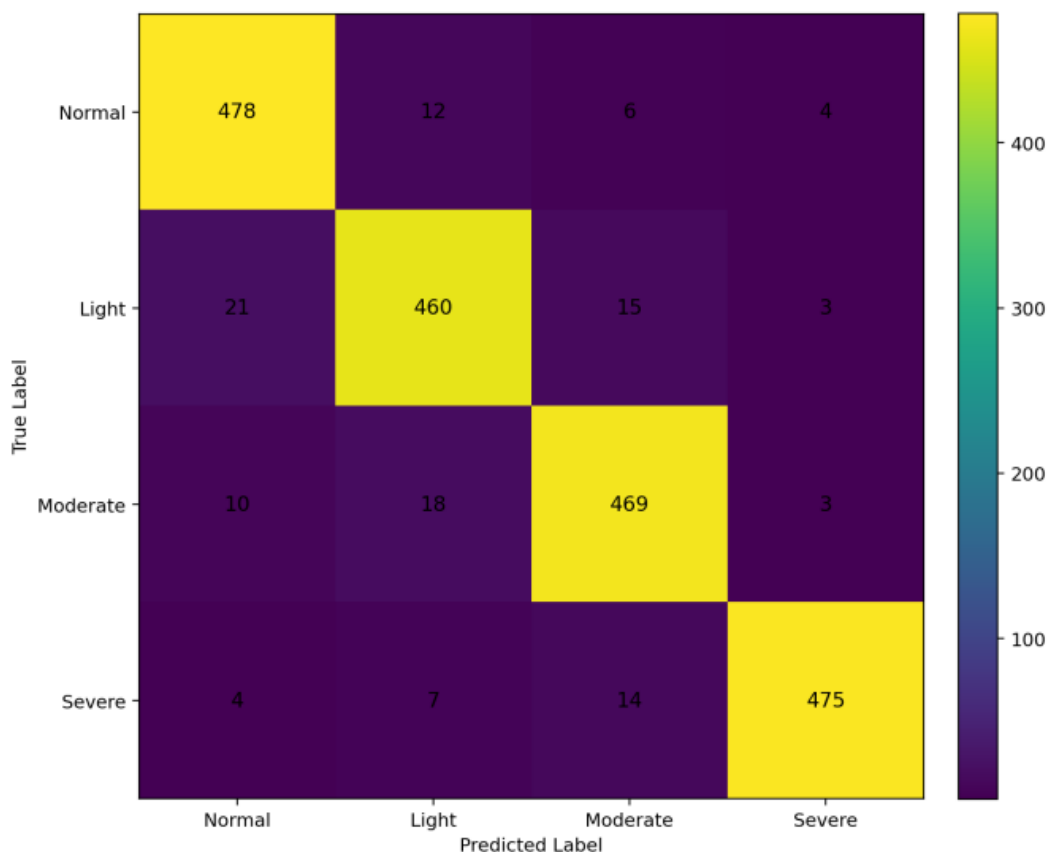


Figure 5: Risk level confusion matrix plot

To test the continuity and robustness of the risk score output, Fig. 6 shows the violin plot of the score distribution of different models on the test set. The scores of the model in this paper mainly focus on 0.08-0.21 on the normal sample, and 0.74 -- 0.93 on the dominant risk sample, with a sufficient interval. In contrast, the distributions of LSTM and BiGRU overlap more obviously, with a large number of crossings in the boundary regions. The score variance of the proposed model is 0.031, which is lower than 0.049 of CNN-LSTM and 0.057 of BiGRU. The mean distance between normal samples and dominant risk samples is 0.63, which is also significantly higher than 0.42 and 0.37 of the baseline model. The results show that the dynamic scoring mechanism can further compress the fluctuation range of the category boundary while maintaining the risk sensitivity, so that the output results are more suitable for entering the linkage decision-making layer without frequent jumps.

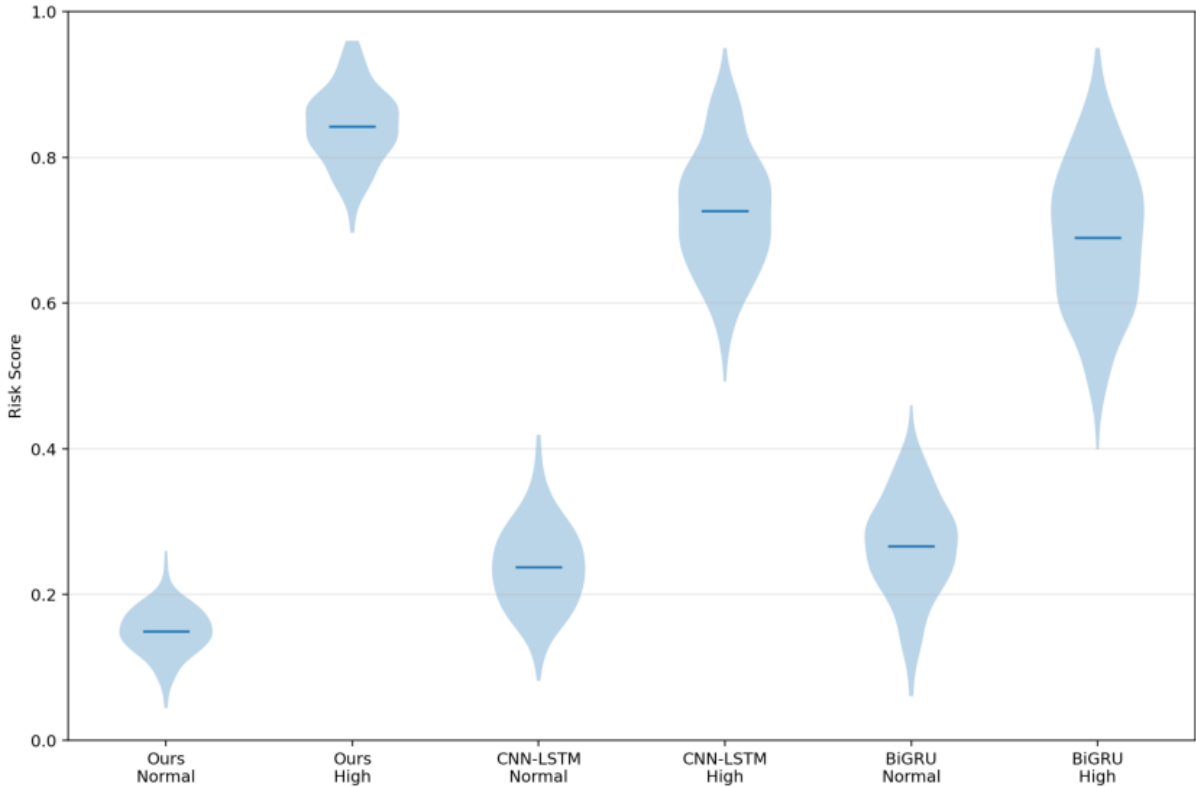


Figure 6: Violin plot of risk score distribution

Based on the results of this section, the risk early warning method fused with time series features shows obvious advantages in accuracy, boundary discrimination and scoring continuity. The unified time series representation provides a continuous state basis for risk identification, and the bidirectional coding and dynamic scoring further strengthen the identification strength of key segments, so that the model can maintain a stable early warning output under the conditions of cross-path, cross-stage and class imbalance. This result shows that the early warning module has been able to fully undertake the continuous risk identification task in cross-border e-commerce logistics, and provide reliable driving signals for collaborative interaction.

4.4 Results of supply chain collaboration driven by logistics risk warning

After the risk warning results enter the collaborative layer, the model needs to further transform the risk level into the linkage action among storage, transportation, replenishment and performance queues. Abnormal states in cross-border e-commerce logistics often do not stay at a single node, but spread to adjacent nodes along the supply chain. Therefore, the core task of the collaboration layer is to map the early warning signals into executable response sequences and resource adjustment strategies. Based on this processing logic, this section analyzes the linkage results from four aspects: node response intensity, overall collaboration performance, regional adaptability and module contribution, so as to test the control effect and structural validity of the risk-early warning driven supply chain collaboration method in actual operation.

In order to show the change of linkage strength of nodes in different regions driven by risk, Fig. 7 shows the thermal distribution of collaborative response among warehousing, transshipment, trunk line and replying nodes. The results show that the store-transfer linkage

strength of the Asia-Europe path reaches 0.83 during peak hours, and the trunk line-replenishment linkage strength of the North American path reaches 0.79, which are higher than the corresponding 0.64 and 0.58 of the rule-driven method. The high-response areas are mainly concentrated in the key node combinations before customs clearance, regional replenishment and terminal delivery, indicating that the proposed method can preferentially enhance the node pairs that really need linkage, thereby reducing the resource consumption caused by invalid scheduling actions. At the same time, the thermal distribution shows that the linkage strength will not spread to all nodes on average, but form a concentrated response around the high-risk, high load and high transmission potential areas, which is consistent with the actual operation characteristics of cross-border logistics.

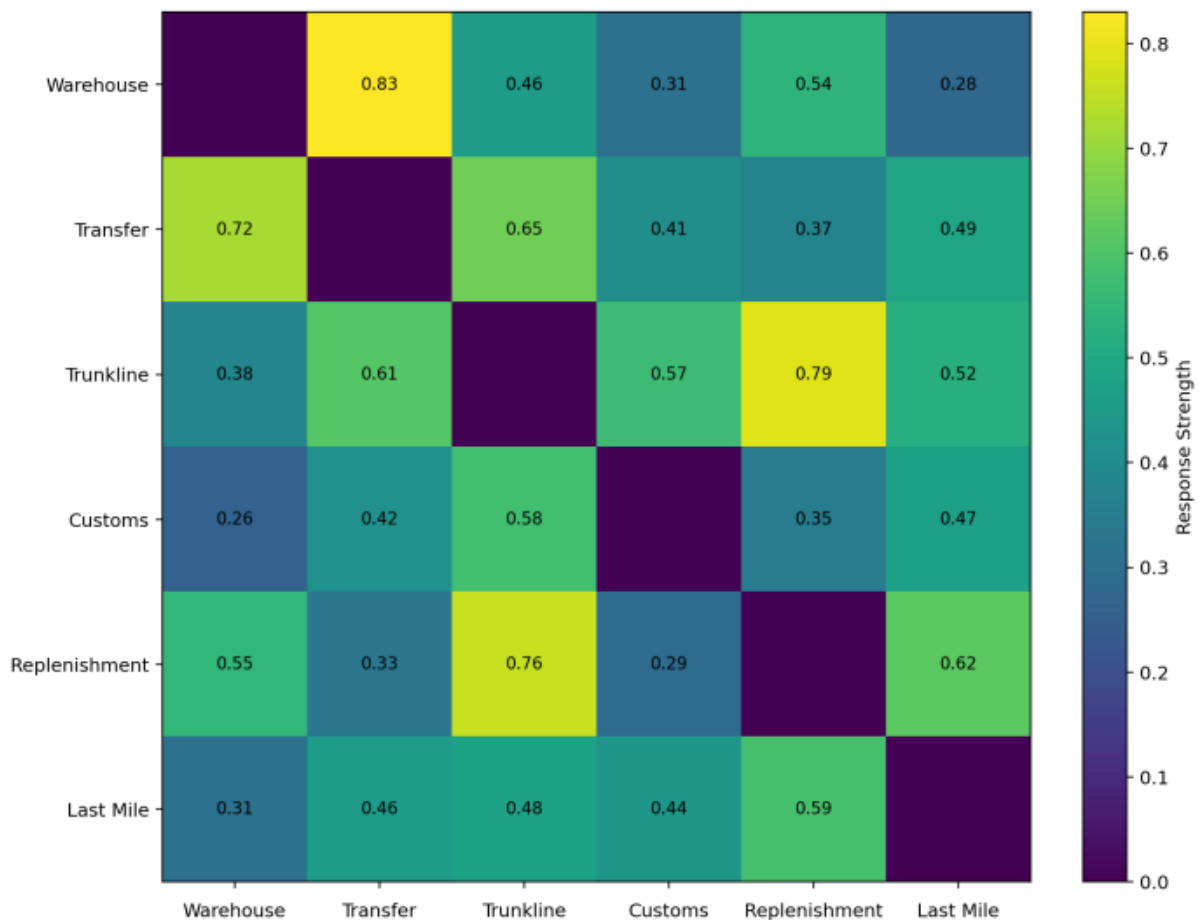


Figure 7: Heat map of supply chain collaborative response intensity

To compare the overall performance of different methods on collaborative results, Table 3 shows the results of the four categories of methods on the key indicators. The average response time of the proposed method is reduced from 2.27 s to 1.84 s, the congestion relief rate is increased from 14.6% to 21.7%, and the performance recovery rate is increased from 82.9% to 90.8%. The cross-node consistency is improved from 81.3% to 92.4%. These data show that the risk-driven collaborative linkage method can not only shorten the response time, but also form a higher consistency between multiple nodes, so that the action output is no longer limited to the local correction of a single node, but forms a more complete supply chain regulation effect.

Table 3: Comparison of overall results for different collaborative methods

Method	Average Response Delay / s	Congestion Relief Rate / %	Fulfilication Recovery Rate / %	Cross-Node Consistency / %
Rule-driven scheduling	2.27	14.6	82.9	81.3
Single-node greedy scheduling	2.11	16.8	84.2	83.8
Risk score direct scheduling	1.97	15.5	86.7	85.9
Proposed method	1.84	21.7	90.8	92.4

To analyze the contribution of each module to the collaborative results, Table 4 presents the ablation experiment results. The average response delay of the complete model is 1.84 s, the congestion relief rate is 21.7%, the performance recovery rate is 90.8%, and the cross-node consistency is 92.4%. After removing the risk-driven mapping, the congestion alleviation rate was reduced to 17.2%, and the performance recovery rate was reduced to 87.4%. After removing linkage benefit evaluation, the average response delay increased to 2.03 s. After removing the action probability ordering, the cross-node agreement drops to 87.1%. Ablation results show that risk-driven, benefit evaluation and action sequencing are not substitutable relationships, but key components that jointly determine the linkage effect. Only if the three are kept at the same time, the warning result can be stably transformed into the cooperative action output with execution order.

Table 4: Ablation experimental results of the collaborative linkage module

Variant	Average Response Delay / s	Congestion Relief Rate / %	Fulfillment Recovery Rate / %	Cross-Node Consistency / %
Full model	1.84	21.7	90.8	92.4
Without risk-driven mapping	1.96	17.2	87.4	88.5
Without coordinated benefit evaluation	2.03	18.1	86.9	89.2
Without action probability ranking	1.98	19.0	88.1	87.1

Based on the results of this section, the logistics risk early-warning driven supply chain collaboration method shows strong advantages in efficiency, resilience and linkage consistency. After linkage mapping, the warning result is no longer just a static classification output, but continues to be transformed into a cooperative control signal under multi-node, multi-action and multi-constraint conditions. The result makes the risk identification and supply chain execution in cross-border e-commerce logistics maintain a closer computational connection, and also shows that the front-end timing analysis and early warning calculation have been able to form an effective support in the back-end collaborative control.

5 Discussion

The results of this paper show that the risk early warning and collaborative interaction framework combining time series feature analysis has strong computational adaptability in cross-border e-commerce logistics scenarios. After the node stay, clearance interval, transit frequency and distribution offset are compressed into a unified state vector by the time series representation module, the phase overlap in the original event stream is significantly reduced, which indicates that position encoding, local convolution and gated update jointly improve the separability of asynchronous logs.

The risk warning module introduces bidirectional time series coding and dynamic scoring mechanism on the basis of unified representation, so that continuous anomalies are no longer segmented into isolated segments, so that it still maintains high recognition stability under the conditions of multi-path, multi-stage and class imbalance. ROC-AUC, F1 value and score distribution all show that the proposed method can distinguish between normal performance, mild deviation and dominant risk states, and maintain high sensitivity to abnormal accumulation in critical periods.

The results of collaborative linkage show that the warning output will form an executable control signal only after entering the process of action benefit evaluation and node sorting. Compared with rule-triggered or single-node greedy scheduling, the improvements in response delay, congestion alleviation rate and performance recovery rate of the proposed method do not come from a single module, but are the comprehensive results after the continuous coupling of timing representation, risk identification and linkage reasoning.

From the perspective of computing, the effectiveness of the framework is mainly reflected in three levels: continuous representation, bidirectional perception and linkage mapping. After discrete logistics events are transformed into a unified state, the state tearing caused by path differences is alleviated. After the risk score enters the context calculation, the identification of delay accumulation and disturbance propagation is more stable. After the risk results continue to be mapped into cooperative actions, the model output can be directly connected to the scheduling execution process.

6 Conclusions

The results of this paper show that the risk early warning and collaborative interaction framework combining time series feature analysis has strong computational adaptability in cross-border e-commerce logistics scenarios. After the node stay, clearance interval, transit frequency and distribution offset are compressed into a unified state vector by the time series representation module, the phase overlap in the original event stream is significantly reduced, which indicates that position encoding, local convolution and gated update jointly improve the separability of asynchronous logs.

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