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Research on dynamic monitoring and collaborative governance system of digital business environment in free trade ports

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SUMMARY: *In order to support the governance of digital business environment in free trade ports, this paper proposes a dynamic monitoring and collaborative governance framework that integrates multi-source data access, time series status recognition, cross-departmental relationship modeling, risk diagnosis and strategy generation. The system processes 1.28 million records in data streams such as administrative approval, customs declaration, tax service, enterprise feedback, logistics circulation, and public complaints, and encodes 36 indicators into a unified time series representation. The timing identification module characterizes fluctuations in market access, service efficiency, contract enforcement, and regulatory response, and a graph-based collaboration mechanism captures inter-departmental dependencies and triggers linkage disposals. Experimental results show that the model achieves 93.4% state recognition accuracy, 0.917 Macro-F1, 91.8% trend consistency rate and 90.6% governance matching degree. The linkage completion rate reaches 90.9%, and the average response time is compressed to 4.2 hours. This framework provides a more effective and computable path for the monitoring and collaborative governance of the business environment of free trade ports under dynamic conditions.*

KEYWORDS: *Free trade port; Digital business environment; Temporal state recognition; Collaborative governance*

1 Introduction

The construction of free trade ports has entered a new stage supported by digital rules, platform services and collaborative response, and the monitoring object of the business environment has expanded from a single approval link to a continuous business chain such as enterprise access, customs clearance and circulation, tax handling, credit feedback and demand disposal. Martins et al. pointed out that digital government can reduce the transaction cost of enterprises through information processing and service reorganization, and improve the level of institutional supply and market facilitation [1]. This change shows that the business environment of free trade ports is not only a static presentation of policy implementation results, but also a cross-platform, cross-departmental and cross-scenario data operation state. Gong et al. studied the action logic and organizational configuration in the transformation of digital government, and believed that the collaborative arrangement in the institutional field would directly affect the operational efficiency of digital services [2]. For the business environment governance of free trade ports, continuous perception of business status, identification of time series fluctuations, and formation of linkage response have

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become the core content of information system design.

Syed et al. proposed that the promotion of public sector digitalization is influenced by data integration capability, organizational collaboration mode and technology adaptation [3]. Escobar et al. sorted out the cases of public sector digital transformation and emphasized that there is a significant coupling relationship between process re-organization, platform architecture and implementation conditions [4]. These studies show that doing business governance is moving from empirical judgment to a computational model that is data-driven and system-supported in parallel. When proposing the GovTech research agenda, Bharosa pointed out that the new government technology system is reconstructing the way of public service supply and promoting the evolution of governance process to platform and intelligence [5]. In the free trade port scenario, enterprise behavior, government data and regulatory records have the characteristics of multi-source heterogeneity, frequent update and close correlation, and it is difficult to describe the environmental change trajectory by only relying on static evaluation.

Breaugh et al. studied leadership and system design in collaborative government digitization, and believed that cross-organizational digital collaboration requires stable structural arrangement and clear assignment of responsibilities [6]. Rukanova et al. proposed that government-enterprise information sharing supported by digital infrastructure can promote public value generation and enhance the computability of business collaboration [7]. Shahaab et al. conducted research on the efficiency of public services supported by blockchain and proved that the trusted data mechanism helps to improve the transparency and execution consistency of service processing [8]. Lourenco studied the monitoring process of government transparency and pointed out that policy accumulation and administrative load need to be identified and adjusted by means of the continuous monitoring framework [9]. Gong et al. further studied the boundary resource design in the digital government platform, and believed that the platform interface, rule configuration and service collaboration capabilities would affect the implementation effect of collaborative innovation [10].

Based on the above research, this paper constructs a dynamic monitoring and collaborative governance system for the digital business environment governance scenario of free trade ports, and integrates multi-source data access, time series state recognition, relationship modeling, risk diagnosis and strategy generation into a unified computing framework, in order to provide a verifiable technical path for real-time perception, linkage disposal and effectiveness evaluation of the business environment. The existing business environment evaluation is mainly based on annual index summary and stage statistics, which is suitable for describing the overall level, but it is difficult to reflect short-term fluctuations in the business chain, event diffusion and departmental response differences.

2 Related work

Focusing on the dynamic monitoring and collaborative governance of digital business environment, the existing research mainly follows the paths of cross-organizational service integration, government digital architecture, data collaboration, open data governance and intelligent technology application. Wouters et al. proposed an integrated digital public service delivery strategy in cross-organizational collaboration networks, and pointed out that service integration needs to form a stable connection between process orchestration, interface sharing and organizational collaboration [11]. Irani et al. studied the impact of legacy systems in the digital transformation of European public management and believed that system heterogeneity would directly change the efficiency of data circulation and the way of platform reconstruction [12]. Susha et al. discussed the collaborative organization mechanism in social issue governance from the perspective of data collaboration ecology, emphasizing the role of conveners in data connection, participation coordination and rule maintenance [13]. Yuan et al. studied the functional positioning of government social media in digital transformation and pointed out that real-time interactive data can enhance governance perception and service feedback capabilities [14]. Ingrams combined machine learning and qualitative comparative analysis in the study of open rule making, indicating that text computing in the process of information management can improve the accuracy of opinion recognition and decision support [15]. These results push the research of digital governance from a single platform construction to a computational framework with multi-agent, multi-source data and intelligent analysis in parallel. In addition, cross-organizational public service research has shown that interface standards, data dictionary unification and event coding consistency will affect the stability of subsequent monitoring models, and the data of government affairs, port business and enterprise demands in the free trade port scenario can only enter the same analysis space after semantic mapping. It can be seen that the related work has gradually promoted the governance research from the institutional description to the technical expression that can be calculated, traced and verified. Table 1 summarizes the research context.

Table 1: Technical orientation and application focus of related research

Reference	Research Focus	Technical Emphasis	Implications for This Study
[11]	Integrated digital public service delivery	Cross-organizational process collaboration	Supports cross-department linkage modeling
[12]	The impact of legacy systems in public administration	Heterogeneous system integration	Supports the design of multi-source data access
[13]	Data collaboration ecosystems and organizational coordination	Data-sharing mechanisms	Supports the construction of collaborative governance relationships
[14]	Government social media and digital transformation	Real-time interactive data analysis	Supports the incorporation of feedback signals
[15]	Machine learning-supported information management	Text computation and recognition	Supports the analysis of complaint and request texts

In terms of dynamic governance mode and expansion of digital tools, Przeybilovicz et al. studied the evolution of smart city governance form in the digital age and pointed out that dynamic governance mode is more dependent on data feedback, platform scheduling and continuous response [16]. Attard-Frost et al. sorted out the practice of AI governance in Canada and believed that the algorithm usage boundary, responsibility division and review mechanism together form the implementation basis of intelligent governance [17]. Fang et al. studied the linkage structure of open government data ecology at the level of data, information and business, indicating that open data platform can promote public information from static release to business collaboration and value reuse [18]. Li et al. proposed an open government data privacy risk identification framework, which integrates data sharing, sensitive attribute identification and risk control into the unified analysis link [19]. Shin et al. systematically analyzed digital tools for citizen engagement and pointed out that multi-terminal interactions, online feedback and participation trajectory records help form continuously updated governance inputs [20]. This kind of research provides a more direct technical reference for state recognition, event feedback and data security control in business environment monitoring. Existing results also show that the data processing for public governance is no longer limited to statistical summary, but gradually introduces graph structure analysis, time series recognition, text mining and rule calculation methods, so that the monitoring objects can be continuously described at the level of event link, response delay and collaborative relationship, which has a high degree of fit with the dynamic operation characteristics of the business environment of free trade ports.

Focusing on the deployment mode of emerging technologies in the public sector, Wamba et al. analyzed the role of blockchain-driven projects in the operation of organizations, and believed that trusted records, shared ledbooks and process traces could enhance the consistency and traceability of cross-departmental business processing [21]. Based on the existing research, it can be seen that the relevant results have provided a relatively complete theoretical and technical support for digital government platforms, open data utilization, intelligent governance tools and organizational coordination mechanisms. However, the research on the business environment scenario of free trade ports still needs to further fit the computational characteristics of high-frequency business flows, cross-departmental interaction links and temporal state changes. Enterprise registration, customs clearance declaration, tax service, complaint acceptance and credit feedback in free trade port have the characteristics of synchronous update, event correlation and clear response time, which are suitable for unified description by combining multi-source data access, time series state recognition, graph relationship modeling and governance strategy generation. Based on this, on the basis of existing research, this paper further expands the data fusion, state calculation and collaborative response mechanism in the digital governance scenario for the business chain of free trade port.

3 Research Methods

3.1 Overall framework of dynamic monitoring and collaborative governance of digital business environment in Free Trade Ports

The operation process of the digital business environment in free trade ports involves multiple continuous links such as government approval, port customs clearance, tax handling, credit feedback, enterprise demands and department disposal. Different links are connected in time and affect each other in business. Therefore, the monitoring system cannot stay at the static index summary level, but needs to form a unified computing structure oriented to event flow, state flow and governance flow.

Based on this scenario, this paper constructs the overall framework of dynamic monitoring and collaborative governance of digital business environment in free trade ports. The framework consists of data access layer, timing perception layer, collaborative computing layer, policy scheduling layer and feedback update layer. The data access layer is responsible for aggregating cross-platform business records and accomplishing timestamp unification, field mapping and theme coding. The time-series perception layer extracts the state features of the business environment according to the sliding window. The collaborative computing layer used the department correlation graph to identify the item diffusion path and linkage strength. The policy scheduling layer generates dispatching actions according to risk level and responsibility relationship. The feedback update layer rewrites the disposal results into the state space for the next round of monitoring and parameter correction.

In order to ensure that the system can maintain computational stability under high-frequency traffic, the framework adopts a closed-loop path of "event input-state decision-cooperative trigger-result writeback". In this way, the monitoring results are no longer independent outputs, but directly enter the governance chain, forming a continuous linkage process for real business scenarios. Fig. 1 presents the structural relations of the overall framework.

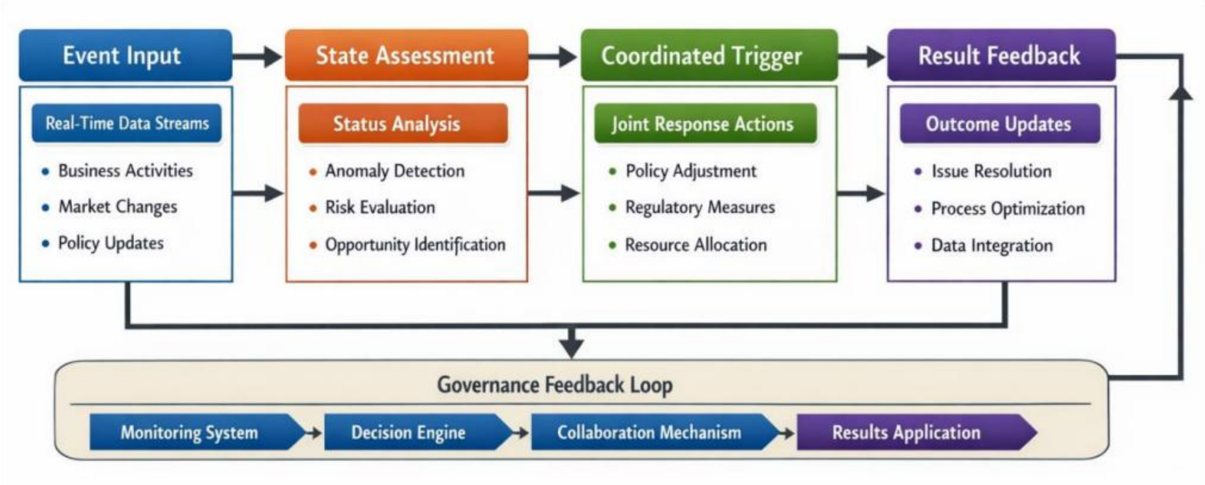

Figure 1: The overall framework of dynamic monitoring and collaborative governance of the digital business environment in Free trade ports

In order to uniformly describe the fusion state of multi-source service data in the same time window, this paper first defines the calculation method of the overall input representation, and writes it as follows:

$$H_t = \phi\left(\sum_{m=1}^{M} \alpha_m W_m X_t^{(m)} + B\right) \tag{1}$$

Here, H_t represents the unified state representation at time t, $X_t^{(m)}$ represents the input matrix of the m traffic source at time t, α_m represents the source weight, W_m represents the mapping matrix, B is the bias term, and $\phi(\cdot)$ is the nonlinear transformation function. This formula is used to compress heterogeneous records such as approval, customs clearance, tax, credit and appeal into the same feature space, and provide a unified input for subsequent time series recognition.

In order to depict the synergy strength formed by the departmental structural relationship and the event propagation in the same time window, this paper further defines the calculation method of the synergy strength matrix as follows:

$$C_t = D_t^{-\frac{1}{2}} A_t D_t^{-\frac{1}{2}} H_t + \lambda (R_t \odot P_t) \tag{2}$$

Here, C_t represents the synergy strength matrix At time t, A_t represents the adjacency matrix of department relations, D_t represents the degree matrix, H_t represents the unified state representation, R_t represents the responsibility mapping matrix, P_t represents the event propagation probability matrix, $\odot$ represents the Hadamard product, and λ is the regulation coefficient. This formula takes the departmental structure relationship and the event diffusion probability into the calculation together, so that the system can identify the key nodes in the linkage chain.

In order to identify the change of synergy strength formed in the process of cross-departmental item flow, this paper further gives the quantitative expression of relationship strength, and specifically expresses the following results:

$$Z_{t+1} = \sigma(UZ_t + VC_t + QY_t + b_z) + \eta\Delta_t \tag{3}$$

where Z_t represents the current system memory state, Y_t represents the governance output result vector, U, V, Q is the parameter matrix, b_z is the bias term, $\sigma(\cdot)$ is the activation function, Δ_t represents the treatment deviation of the current round, η is the update step. This formula is used to write the collaborative response results and deviation feedback into the state space synchronously, so as to improve the recognition consistency of subsequent rounds.

At the framework level, instead of separating monitoring, governance, and feedback into separate modules, we put all three together on the same computing link. In this way, the time continuity of business environment changes can be preserved, and the structural characteristics of cross-sectoral collaboration can also be reflected. The overall framework provides a unified basis for subsequent data feature construction, state recognition and policy generation, and makes the governance system computable and verifiable for real-time scenarios.

3.2 Multi-source data access and feature construction for the business environment of free trade ports

Upon completion of the underlying access, the system converts the raw records into standard event units. Each event unit contains the subject identity, event type, processing department, occurrence moment, status label, and feedback result. Subsequently, this paper constructs a unified input from four dimensions of numerical features, textual features, relational features and time series features. The numerical characteristics describe the explicit indicators such as the quantity of parts, the overtime rate, the rejection rate, and the abnormal fluctuation. The emotional intensity and theme distribution of enterprise appeals were extracted from text features. Relationship characteristics reflect the depth and coupling degree of items between departments. Time series features are used to represent the mean shift, trend shift and burst change intensity in the window period.

In order to weaken the interference caused by different dimensions and abnormal fluctuations on the index distribution, this paper first gives the robust standardization processing method, and specifically expresses the following formal values:

$$\tilde{x}_{i,t} = \frac{x_{i,t} - \mathrm{Med}(x_i)}{\mathrm{IQR}(x_i) + \epsilon} \tag{4}$$

Here, $\tilde{x}_{i,t}$ represents the normalized result of the i index at time t, $\mathrm{Med}(x_i)$ represents the median of this index, $\mathrm{IQR}(x_i)$ represents the interquartile range, and ϵ is the smoothing term. This formula is suitable for dealing with the phenomenon of skewed distribution and local spikes that are common in business data.

In order to highlight the high-contribution semantics in the appeal text, this paper uses the attention weighting method to construct the semantic representation of the text:

$$s_t = \sum_{j=1}^{L} \beta_{j,t}\ E(w_j), \quad \beta_{j,t} = \frac{\exp(e_{j,t})}{\sum_{r=1}^{L} \exp(e_{r,t})} \tag{5}$$

where s_t represents the semantic vector of the text at time t, $E(w_j)$ represents the embedding representation of the j word, $\beta_{j,t}$ represents the attention weight, $e_{j,t}$ represents the importance score of the term, and L represents the number of terms. This formula is used to highlight the high-contribution semantics related to approval, customs clearance, taxation and cashing in the appeal text.

In order to disseminate the connection relationship and event dependency information between departments, the graph propagation process of relationship features is incorporated into the unified representation, and is specifically written as the following result:

$$g_t^{(l+1)} = \rho\left(\widehat{A}_t g_t^{(l)} W_g^{(l)} + b_g^{(l)}\right) \tag{6}$$

Here, $g_t^{(l)}$ represents the relationship feature of the l layer, $\widehat{A}_t$ represents the normalized department relationship matrix, $W_g^{(l)}$ and $b_g^{(l)}$ represent the parameter matrix and bias term, respectively, and $\rho(\cdot)$ is the activation function. This formula is used to propagate the department connection information and the event dependency information, so that the relationship characteristics can express the collaborative path.

After the above processing, the multi-source original records are converted into a unified feature representation that is traceable, interpretable and reusable. The input constructed in this way can not only support the subsequent temporal state recognition, but also retain the complete connection between the source of the item, the departmental link and the feedback semantics, and reserve the necessary computational clues for the subsequent collaborative triggering and governance policy generation.

3.3 Time series state identification model of digital business environment in Free Trade ports

The digital business environment of free trade ports is not static on the time axis, but is affected by the pace of policy implementation, the speed of business flow, the density of enterprise feedback and the response efficiency of departments. In order to identify such dynamic changes, this paper constructs a time series state recognition model to determine the operation state of the business environment in continuous Windows. The model output includes four kinds of state labels: normal, fluctuation, tightening and warning, and gives the corresponding confidence and transition trend.

The model input is the uniform window tensor obtained in the previous section. The bottom encoder is responsible for extracting the short period changes within the local time window, and the upper aggregation unit further captures the trend information across the window. Considering that the state of the business environment is greatly affected by a few key events, the model adds an attention selection mechanism in the aggregation stage, so that high-impact time slices such as approval delays, customs clearance backlogs, tax refunds and centralized complaints receive higher weights. Fig. 2 illustrates the model structure. The model consists of three parts: dual-scale temporal coding, attention aggregation and state classification. The front end receives multi-source feature Windows, the middle part completes local representation and cross-time information extraction, and the back end outputs state categories and trend tips.

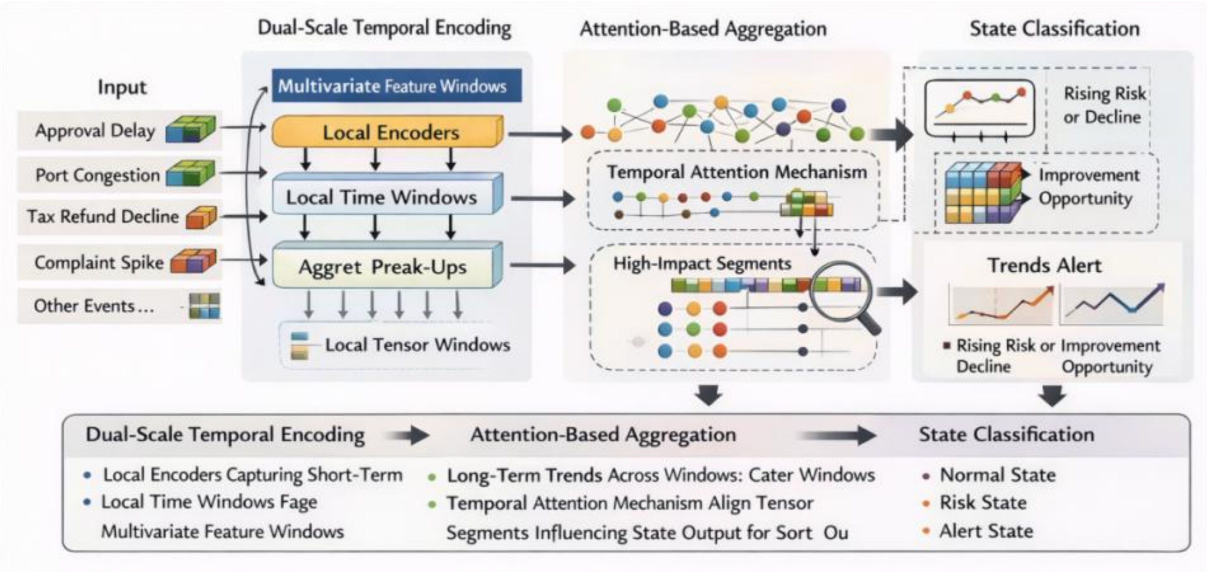

Figure 2: Time-series state identification model of digital business environment in free trade ports

In order to organize multi-class features into a unified time-series window input tensor, this paper further expresses the final input construction method as the following specific form result numerical term:

$$h_t = \Gamma_t \odot \tanh(W_h X_t + U_h h_{t-1} + b_h) \tag{7}$$

Here, h_t represents the hidden state at time t, X_t represents the current input window feature, h_{t-1} represents the state at the previous time, W_h and U_h are parameter matrices, b_h is the bias term, Γ_t represents the gating coefficient, $\odot$ represents element-wise multiplication. This formula is used to preserve valid information and suppress short-time noise in the temporal recursion.

In order to extract continuous offset information across time Windows and enhance the ability of trend identification, this paper further expresses the trend aggregation method as the following specific form result value:

$$q_t = \sum_{r=0}^{R-1} K_r \, h_{t-r} + b_q \tag{8}$$

Here, q_t represents the trend aggregation representation at time t, K_r represents the r convolution kernel weight, R represents the length of the convolution receptive field, and b_q is the bias term. This formula is used to extract continuous migration patterns across time Windows, thereby enhancing the ability of the model to recognize phasic changes.

In order to complete the state discrimination output according to the importance of different time slices, the calculation method of the final state probability is further expressed as the following result value:

$$p_t = \mathrm{softmax}\left(W_p \sum_{k=1}^{\tau} \alpha_{k,t}\, q_k + b_p\right), \quad \alpha_{k,t} = \frac{\exp(v^\top q_k)}{\sum_{j=1}^{\tau} \exp(v^\top q_j)} \tag{9}$$

Here, p_t represents the state probability distribution of the current window, $\alpha_{k,t}$ represents the attention weight of the k time slice, W_p represents the classification mapping matrix, b_p is the bias term, and v is the attention parameter vector. This formula is used to determine the state according to the importance of the time slice, so that the key fluctuations can be highlighted more accurately.

From the recognition results, the model not only outputs the current state, but also retains the state transition trend and the contribution degree of key time slices. In this way, the subsequent governance module can directly read the direction of change, abnormal sources and high-impact links in the current period, so as to realize the smooth connection from monitoring to collaborative disposal. The model also makes the dynamic evolution of the business environment of free trade ports obtain a clearer computational expression, which lays a stable foundation for subsequent risk diagnosis and governance strategy generation.

3.4 Cross-departmental governance relationship modeling and coordination trigger mechanism

The digital business environment governance of free trade ports is not a single-department serial process. Approval, customs clearance, tax, credit, demand disposal and park services continue to interact in the same business cycle, and the delay of a single item often changes the processing rhythm of subsequent nodes. In order to transform this linkage relationship into a computable structure, we map departments, events and disposal actions into a heterogeneous governance graph, and update node attributes and edge weights in a continuous time window.

The nodes in the governance graph represent the business units with responsibility boundaries, and the edges represent the relationships such as transaction transfer, parallel consultation, joint audit and result writeback. Different from the static flow chart, the relationship graph constructed in this paper preserves three types of information at the same time: time order, business intensity and historical collaboration performance, which enables the model to distinguish between regular collaboration links and high-impact diffusion links. In this way, local exceptions are no longer just a single point of fluctuation, but can be tracked and quantified along the responsibility structure and business path.

Fig. 3 shows the heterogeneous graph expression form of the above cross-departmental governance relationship. The graph integrates business events, governance nodes and collaboration edges into the same structure, so that the propagation process of local exceptions on the responsibility chain and the business chain can be continuously tracked, and provides a structural basis for the subsequent edge weight update, path influence degree calculation and collaborative trigger judgment.

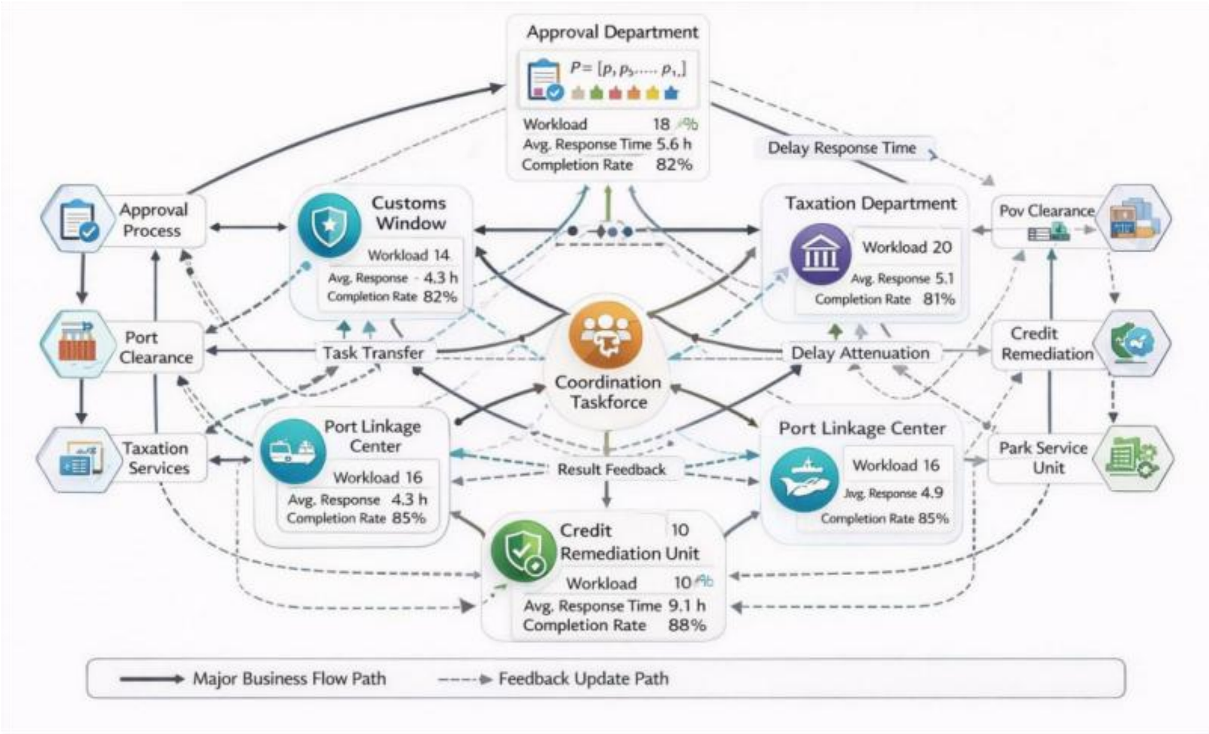

Figure 3: Schematic diagram of the cross-sectoral heterogeneous governance diagram structure of the digital business environment in the Free Trade Port

Under the premise of keeping the relationship between departments changing synchronously with the business load, the cooperation frequency, response time difference and stability are jointly written into the edge weight update process, which is calculated as follows:

$$a_{ij}^{(t)} = \mu_1 \frac{f_{ij}^{(t)}}{\sum_r f_{ir}^{(t)}} + \mu_2 \exp(-\delta\tau_{ij}^{(t)}) + \mu_3\kappa_{ij}^{(t)} \tag{10}$$

Here, $a_{ij}^{(t)}$ represents the edge weight from node i to nodej at time t, $f_{ij}^{(t)}$ represents the cooperation frequency in this time window, $\tau_{ij}^{(t)}$ represents the average response interval, $\kappa_{ij}^{(t)}$ represents the historical cooperative stability, μ_1 to μ_3 are the combination coefficients, and δ is the time decay factor. This formula is used to compress the service frequency, processing time difference and history performance into dynamic edge strength.

After obtaining the dynamic edge structure, the system continues to propagate the node state and responsibility chain information to identify the amplification path of local fluctuations in the linkage network. The propagation process is as follows:

$$h_i^{(t,l+1)} = \sigma\left(\sum_{j\in\mathcal{N}(i)} \alpha_{ij}^{(t,l)} W^{(l)} h_j^{(t,l)} + b^{(l)}\right) \tag{11}$$

where $h_i^{(t,l+1)}$ represents the representation vector of node i in the l layer at time t, $\mathcal{N}(i)$ represents the neighborhood set of node i, $\alpha_{ij}^{(t,l)}$ represents the attention coefficient, $W^{(l)}$

and $b^{(l)}$ are the parameter matrix and bias term, and $\sigma(\cdot)$ is the activation function. This formula is used to propagate responsibility information and coordination status in heterogeneous governance diagrams.

In order to describe the hierarchical influence formed when the event anomaly diffuses outward along the collaboration path, this paper introduces the path influence degree calculation method with time decay, and its expression is as follows:

$$\psi_p^{(t)} = \sum_{r=1}^{|p|} \omega_r \, a_{v_{r-1}v_r}^{(t)} \exp(-\zeta \Delta t_r) \tag{12}$$

where $\psi_p^{(t)}$ represents the diffusion influence degree of path p at time t, $|p|$ represents the path length, v_r represents the r node on the path, ω_r represents the position weight, Δt_r represents the processing time difference between adjacent nodes, and ζ is the attenuation factor. This equation is used to measure the conduction strength of a cooperative path to the subsequent nodes.

When the abnormal density, retention depth and link diffusion strength increase at the same time, the system needs to automatically determine whether to enter the linkage disposal stage. The trigger function is defined as follows:

$$g_t = \mathbb{I}\left(\chi_t + \nu_1 \bar{d}_t + \nu_2 \bar{q}_t + \nu_3 \psi_{max}^{(t)} > \theta_t\right) \tag{13}$$

Here, g_t represents whether the collaborative linkage is triggered at time t, $\mathbb{I}(\cdot)$ is the indicator function, χ_t represents the abnormal density score, $\bar{d}_t$ represents the average retention depth, $\bar{q}_t$ represents the load pressure, $\psi_{max}^{(t)}$ represents the maximum path influence degree, ν_1 to ν_3 are the weight coefficients, and θ_t is the dynamic threshold. This formula is used to compress multi-class disturbances into linkage trigger decision conditions.

This section transforms the cross-departmental governance relationship from a descriptive structure into a dynamic graph calculation object. The subsequent risk diagnosis module can directly call the edge weight, propagation path and trigger result, so that the anomaly identification, linkage determination and task allocation are in the same traceable calculation link.

3.5 Business risk diagnosis and governance strategy generation method for free trade ports

The risk diagnosis module runs directly on the timing state recognition results. After receiving the current state probability, the strength of the relationship graph, the enterprise feedback semantics and the historical disposal records, the system first calculates the anomaly score of the event, and then determines the risk level and the expected diffusion range. The diagnostic object here is not the deviation of a single index, but the comprehensive disturbance of the event in the three dimensions of time, structure and feedback.

Fig. 4 shows the process of risk diagnosis and strategy generation. The left input contains state probability vector, relationship chain strength and feedback semantic vector. The middle unit completed risk aggregation, level mapping and constraint screening in turn. The right output generates action sequences such as supervision, dispatching, parallel consultation and result writing back. The arrow in the figure represents the data flow direction, and the dashed loop represents the priority correction path after the execution result is returned to the model.

Therefore, the whole structure is not a one-way decision, but a closed-loop decision chain with continuous update ability.

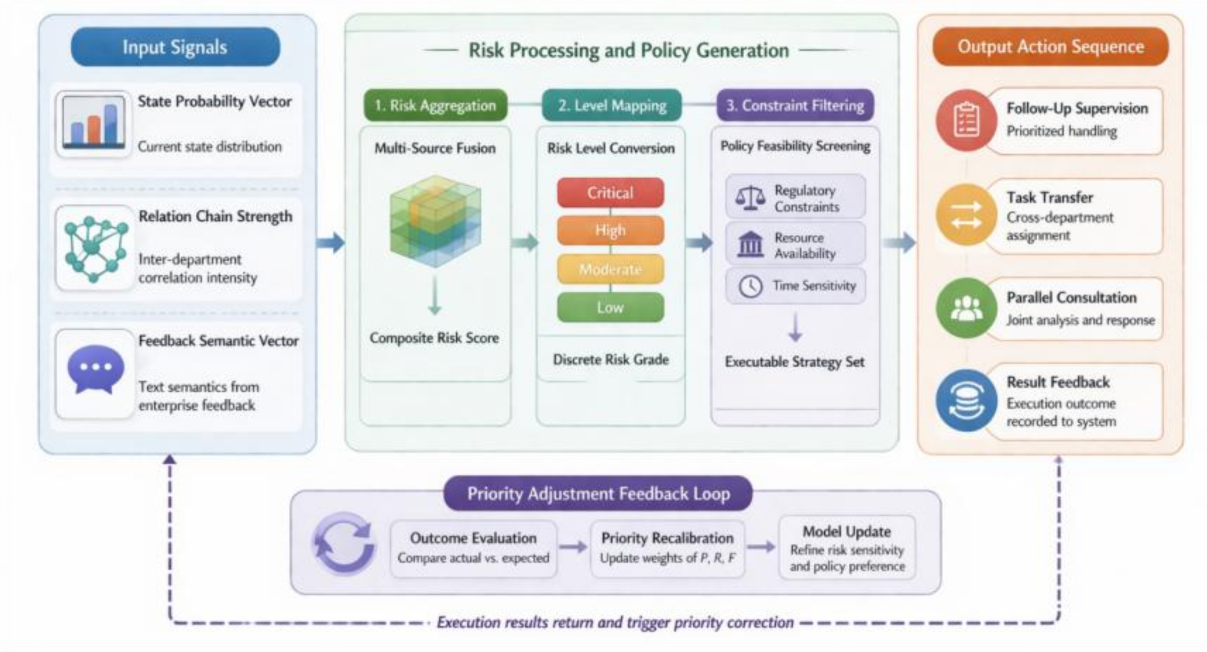

Figure 4: Business risk diagnosis and governance strategy generation process in free trade ports

In order to unify the semantics of state output, relation perturbation and feedback into the same diagnosis space, this paper defines the calculation method of the comprehensive risk score as follows.

$$R_t = \xi_1 w_s^T p_t + \xi_2 w_g^T c_t + \xi_3 w_e^T e_t \tag{14}$$

Here, R_t represents the comprehensive risk score at time t, p_t represents the state probability vector, c_t represents the collaborative structure feature, e_t represents the enterprise feedback semantic vector, w_s,w_g, w_e are the corresponding weights, and ξ_1 to ξ_3 are the combination coefficients. This formula is used to compress multi-source risk signals into a unified score.

After obtaining the risk value at the current time, the system continues to estimate the future impact formed when the anomaly diffuses outward along the cooperative structure in the following way:

$$\widehat{R}_{t+\Delta} = R_t + \sum_{j\in\mathcal{N}} \varpi_j \exp(-\lambda\Delta)\, a_j^{(t)} R_j^{(t)} \tag{15}$$

Here,$\widehat{R}_{t+\Delta}$ represents the prediction risk of the future Δ time window, $R_j^{(t)}$ represents the risk value of neighboring node j at time t, $a_j^{(t)}$ represents the adjacent influence strength, ϖ_j is the propagation weight, and λ is the time decay factor. This equation is used to estimate the degree of spillover of local anomalies in subsequent links.

Due to the differences in costs, rules and responsibility boundaries between candidate actions, policy selection needs to complete a joint optimization between benefits and constraints, which is expressed as follows:

$$\pi_t^* = \arg\max_{\pi \in \Pi} [U(\pi \mid R_t) - \beta_1 C(\pi) - \beta_2 V(\pi)] \tag{16}$$

where π_t^* represents the optimal governance policy, Π represents the set of candidate policies, $U(\pi \mid R_t)$ represents the utility score of the policy under the current risk condition, $C(\pi)$ represents the execution cost, $V(\pi)$ represents the rule conflict penalty term, and β_1, β_2 are the regulation coefficients. This formula is used to filter the governance actions that are more suitable for the current scenario.

After this step, the risk diagnosis results no longer stay at the monitoring conclusion level, but can directly generate governance actions with responsibility path, execution timing and writeback markers. The policy output formed in this way is interpretable, executable and updatable at the same time, which is more suitable for continuous governance in high-frequency business interaction scenarios of free trade ports.

3.6 Indicator system for evaluating the effectiveness of collaborative governance of digital business environment in Free Trade Ports

The evaluation of collaborative governance effectiveness should not only look at the single accuracy rate, nor the response time. In this paper, the identification reliability, collaborative responsiveness, governance matching degree and operation stability are incorporated into the same evaluation system to measure the overall performance of monitoring, linkage and disposal. With this setup, algorithm output and business execution can be compared on the same scale.

The evaluation system simultaneously receives status recognition results, policy assignment logs, department receipt records and enterprise feedback information. The system first completes the normalization of indicators, and then summarizes the stage scores and comprehensive scores according to the dimension weights. In order to avoid the extreme value of a single window amplifying the overall judgment, this paper introduces a fluctuation penalty term in the general evaluation stage, so that the evaluation results are closer to the continuous operation state.

Table 2 shows the composition of the effectiveness evaluation index system. The first column in the table is the dimension name, the second column is the corresponding indicator, and the third column gives the indicator meaning. The identification index reflects whether the model is stable, the response index reflects whether the linkage is timely, the matching index reflects whether the policy output conforms to the responsible link, and the stability index reflects the fluctuation degree of the system under different time Windows and different business loads.

Table 2: Indicator system for evaluating the effectiveness of collaborative governance of digital business environment in free trade ports

Dimension	Metrics	Meaning
Recognition Reliability	Accuracy, Macro-F1, Trend Consistency Rate	Measures the consistency between state recognition results and actual records
Collaborative Responsiveness	Average Response Time, Coordination Completion Rate, Closed-Loop Resolution Rate	Measures the execution efficiency and completion depth of collaborative actions
Governance Matching Degree	Strategy Adoption Rate, Responsibility Consistency Rate, Path Matching Degree	Measures the alignment between strategy outputs and business rules
Operational Stability	Stability Index, Window Volatility Rate, Cross-Cycle Deviation	Measures the fluctuation level of the system under different load conditions

In the unified processing of evaluation indicators of different dimensions, this paper adopts the subsection normalization method, which is expressed as follows:

$$s_i = \begin{cases} \dfrac{x_i - \min(x_i)}{\max(x_i) - \min(x_i)}, & benefit\backslash\ type \\ \dfrac{\max(x_i) - x_i}{\max(x_i) - \min(x_i)}, & cost\backslash\ type \end{cases} \tag{17}$$

Here, s_i represents the normalized score of the i index, x_i represents the original index value, and $\max(x_i)$ and $\min(x_i)$ represent the maximum and minimum value of the index in the sample, respectively. This formula is used to unify the evaluation indexes of different dimensions into a comparable interval.

In order to combine recognition accuracy, macro-average F1 and trend consistency into the same dimension score, this paper defines the calculation formula of recognition reliability as follows:

$$Q_{rec} = \alpha_1 Acc + \alpha_2 F_1 + \alpha_3 T_c \tag{18}$$

Here, Q_{rec} represents the recognition reliability score, Acc represents the accuracy, F_1 represents the macro average F1 value, T_c represents the trend consistency rate, and α_1 to α_3 are the weight coefficients. This formula is used to comprehensively evaluate the judgment ability of the monitoring model.

The evaluation system given in this section can not only serve experimental comparison, but also serve model writeback. When monitoring accuracy, linkage efficiency, strategy matching and operation stability are put into the same evaluation framework, the subsequent result analysis has a unified scale, and the system iteration has a more clear feedback basis.

4 Results and discussion

4.1 Experimental scheme and parameter setting of digital business environment monitoring in Free Trade Port

The experiment part relies on the self-built free trade port digital business environment data set. The data sources included approval log, customs declaration record, tax acceptance flow, enterprise credit change, hotline work order text and park service feedback. A total of 1.28 million time series records were formed, covering the continuous business cycle from January 2023 to June 2024. The system aligns events at the hourly granularity and constructs the monitoring sample with a 7-day sliding window. The training set, validation set and test set were divided by 7:1:2. All text data were processed by word segmentation, denoising and topic merging, and structural fields were unified to complete missing and abnormal verification.

The model is trained on Ubuntu 22.04 environment, using Python 3.10, PyTorch 2.2 and CUDA 12.1. The hardware platform is Intel i9-13900K, RTX 4090 and 128 GB RAM. AdamW was chosen as the optimizer, the initial learning rate was set to 1×10-4, the batch size was 32, the number of training rounds was 80, and the number of early stopping rounds was set to 10. According to the definition above, the evaluation indicators mainly include Accuracy, Macro-F1, trend consistency rate, linkage completion rate, governance matching degree and average response time. In order to avoid the same event being counted repeatedly at the window boundary, the system generates a unique index based on the combination of enterprise subject identification, event code and timestamp, and synchronously retains the department routing sequence in the graph calculation phase.

To ensure that the experimental conditions are consistent across different modules, the running platform, window length, number of training rounds, and random seed Settings are unified in this paper. The random seed was fixed to 42, and all experiments were repeated for five times and the average results were taken. Table 3 shows the core experimental environment and parameter configuration. The window length in the table is set to 7 days, mainly considering that the business environment of the free trade port has obvious rhythms of approval, application and appeal aggregation in the weekly period. The batch size is set to 32, which is the result of achieving a balance between video memory occupation and training stability. The 80 rounds of training and 10 rounds of early stopping were used to avoid overfitting and maintain smooth convergence of the validation curve.

Table 3: Experimental environment and core parameter Settings

Item	Configuration
Operating System	Ubuntu 22.04
Development Environment	Python 3.10, PyTorch 2.2, CUDA 12.1
Hardware Platform	i9-13900K, RTX 4090, 128 GB RAM
Time Granularity	1 h
Window Length	7 d
Optimizer	AdamW
Initial Learning Rate	1×10^{-4}
Batch Size	32
Training Epochs	80
Early Stopping Patience	10 epochs

Under the parameter conditions shown in Table 3, the monitoring module, the collaboration module and the policy module all complete the calculation within the same data partition and the same training framework. In this way, the subsequent time series evolution results, collaborative governance response results and model validity verification can be established on a consistent experimental basis, avoiding additional offset caused by environmental differences. The overall experimental scheme not only retains the timing characteristics of the free trade port business chain, but also meets the needs of subsequent model comparison and result review.

4.2 Analysis of time series evolution results of business environment in free trade ports

On the test set, the sequential state recognition module gives a relatively stable evolution trajectory for continuous service Windows. Firstly, the system maps the approval efficiency, customs clearance time, tax refund rate, credit change frequency and demand heat into a unified state space, and then outputs four types of labels: normal, fluctuation, tightening and early warning every week. The results show that the sample maintains a normal and fluctuating alternating distribution in most time Windows, and only shows a continuous tightening state near the quarterly declaration peak, the centralized promotion clearance cycle and the policy switching node. Fig. 5 uses heat maps to present the intensity changes of the four categories of states in a continuous window of eighteen weeks. The results showed that the density of states increased significantly in week 6, week 11 and week 15, and the intensity of tightening state reached 0.74 in week 6, 0.81 in week 11, and 0.86 in week 15.

Correspondingly, the intensity of normal state decreases to 0.29, 0.24 and 0.18, respectively. This shows that risk does not appear discrete, but forms a continuous accumulation in a specific business period.

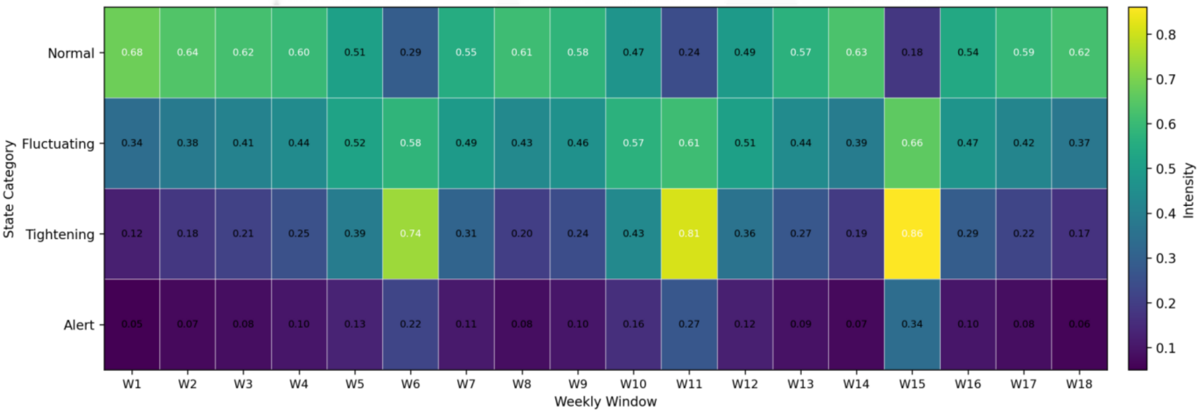

Figure 5: Heat map of time series state of business environment in free trade ports

According to the state transition law, the transition probability from normal state to fluctuation state is the highest, reaching 0.27, which indicates that most disturbances are manifested as local link fluctuations first. The transition probability from the fluctuation state to the tightening state is 0.18, which indicates that when the load and delay are accumulated at the same time, the local event is more likely to rise to the overall pressure. The transition probability of the tightening state to the warning state is 0.11, which is low, but once the system enters the interval, the frequency of triggering linkage governance increases significantly. Combined with the original data in the window, it can be seen that the average processing time of approval in the sixth week increased from 18.6 hours in the base period to 24.9 hours, and the tax refund rate increased from 4.8% to 7.2%. In the 11th week, the average detention time of customs clearance reached 31.4 h, and the density of enterprise consultation increased to 1.37 times of the baseline value. In week 15, high-frequency words such as "waiting", "repeated submission" and "no feedback" increased significantly in the appeal text, and the feedback delay index rose synchronously. Thus, it can be judged that a high consistency is maintained between the state lifting and the real business rhythm.

Fig. 6 uses box plots to show the distribution of the comprehensive risk scores under different Windows. The results showed that the median of the comprehensive risk score at week 6 was 0.63, the lower quartile was 0.58, and the upper quartile was 0.69. At the 11th week, the median value increased to 0.71, and the box range expanded to 0.64-0.77. In week 15, the median and the upper and lower bounds are higher than the other Windows, reaching 0.78. In contrast, the median of week 2, week 8 and week 14 is 0.34, 0.39 and 0.36, respectively, and the length of the box is significantly shorter, indicating that although there are fluctuations in the business volume in these stages, the overall operation is still stable. In Fig. 5, a small number of high outliers also appear in week 11 and week 15, with the highest risk scores reaching 0.84 and 0.89 respectively, indicating that the differentiation between links with different events is more obvious within the high load period.

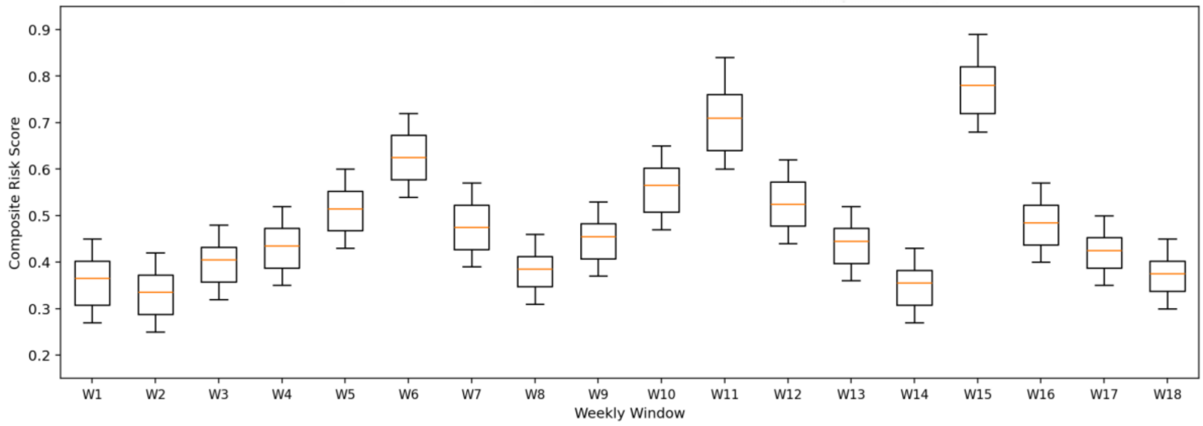

Figure 6: Boxplots of integrated risk scores for different time Windows

After further splitting by indicator layer, it can be seen that the contribution of approval processing time to state change is higher in the early stage, the clearance congestion degree and demand density are more active in the middle and late stage, and the proportion of credit anomalies continues to rise in a few Windows. The trend consistency rate of the model output reaches 91.8%, which indicates that the system's judgment of the continuous evolution direction keeps a high agreement with the real business record. On the whole, the time series evolution results not only reflect the stage tension under the peak of business, but also reveal the dominant relationship between multiple types of indicators in different Windows, which provides a clearer time basis for subsequent collaborative response. From the perspective of perimeter continuity, the system maintains a good state smoothness between adjacent Windows, and there is no unfounded jump output. Two weeks before the warning window appears, the model has given an advance signal through the continuous rise of the fluctuation state, indicating that the recognition results can not only be used for post-hoc interpretation, but also for service pre-judgment and linkage preparation. This evolution structure along the time axis provides a stable reference for the advance configuration of governance resources, and also enhances the pertinence and verifiability of subsequent decisions.

4.3 Analysis on response effect of cross-departmental collaborative governance

The cross-departmental collaborative governance response module shows a strong linkage adaptation ability in the test. The system automatically generates dispatching sequences according to status identification results, event propagation paths and department load levels, and continuously tracks the response chain. The results show that after the collaborative trigger mechanism is included, the first sound time decreases from 6.8 hours to 4.2 hours under the traditional rule assignment, the linkage completion rate increases from 78.6% to 90.9%, and the closed-loop disposal rate increases to 88.7%. These changes show that the task flow after relationship modeling no longer depends on a single point of manual judgment, but can complete a more accurate node selection according to the chain of responsibility and diffusion strength.

Fig. 7 uses a scatter plot to show the linkage distribution of different event types in two dimensions of average response time and responsibility consistency rate. The results show that the items of approval delay are mainly concentrated around 3.9 hours and 92.4%, indicating that the response rate of this type of items is fast and the responsibility consistency rate is high. The backlog items of customs clearance are mainly distributed around 4.6 hours and 90.5%, indicating that the coordination chain is longer and the processing load is higher. Tax refund and credit repair events are concentrated around 4.3-4.4 h and 91.0%, indicating that these events still maintain a relatively stable matching level in the process of writeback confirmation. The three types of events form a clear distribution boundary in the two-dimensional space, indicating that there are obvious differences in the collaborative governance response of different business types.

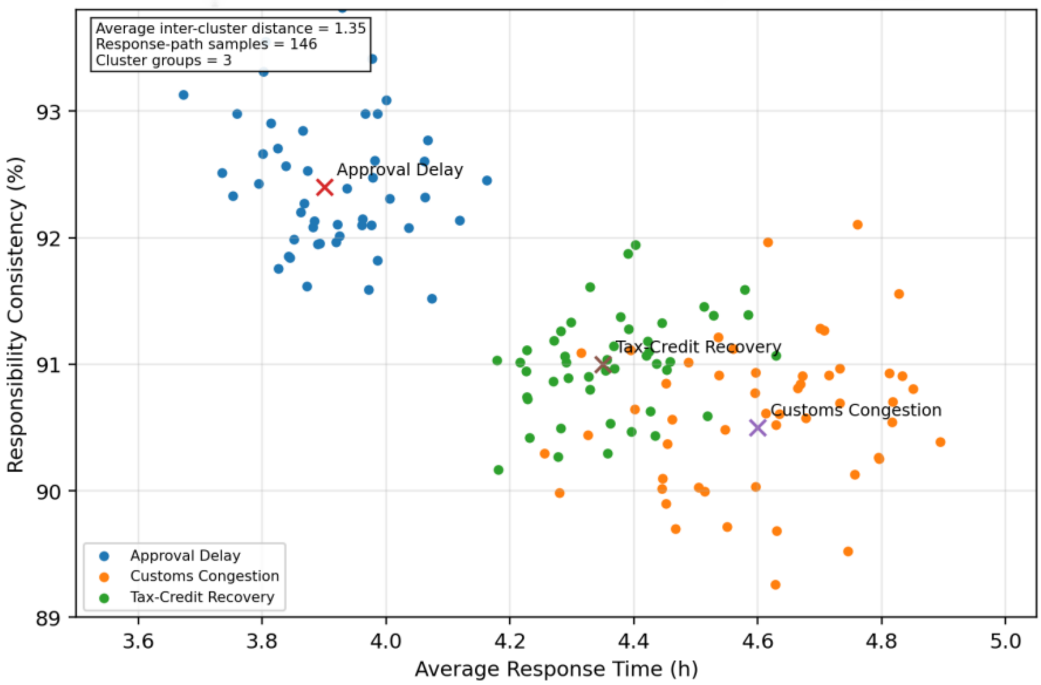

Figure 7: Scatter plot of collaborative governance responses across sectors

In order to further verify the linkage results, this paper counts the response time, linkage completion rate and responsibility consistency rate under different categories of events, and Table 4 shows the specific comparison results. The results show that the average response time of approval delay items is the lowest, which is 3.9 h. The linkage completion rate reaches 91.7%, and the responsibility consistency rate is 92.4%. The average response time of customs clearance backlog items was 4.6 h. Although the link was longer, the linkage completion rate remained at 89.8%. The response time of tax refund items was 4.3 hours, and the completion rate and responsibility consistency rate were 90.6% and 91.2%, respectively. The appeal aggregation items were affected by text differences and expression diversity, and the average response time was 4.8 hours, the linkage completion rate was 87.5%, and the responsibility consistency rate was 88.9%. It can be seen that the more structured items are, the more stable the linkage effect is, and the improvement of text-driven items is mainly reflected in the accuracy of responsibility mapping.

Table 4: Comparison of collaborative response effects for different item categories

Issue Category	Average Response Time / h	Coordination Completion Rate / %	Responsibility Consistency Rate / %
Approval Delay	3.9	91.7	92.4
Customs Backlog	4.6	89.8	90.5
Tax Return Rejection	4.3	90.6	91.2
Complaint Concentration	4.8	87.5	88.9

From the overall operation results, the collaborative governance response is not simply to speed up the processing speed of a node, but to reduce invalid dispatching, shorten the waiting interval and improve the matching degree of responsibility through path reconstruction. The results of the appeal experiment show that the system has good structural adaptability in the first round diversion, core node identification and link convergence. The linkage result formed in this way not only improves the disposal efficiency, but also provides a clearer structure basis for the subsequent effectiveness verification, and makes the governance response process have stronger traceability and result interpretability.

4.4 Model validity verification and governance matching degree verification

The validity test of the model was carried out around three main lines: overall performance, module contribution and governance matching. This paper compares the variants of the full model, removing the relationship modeling module, removing the collaborative trigger module and removing the policy update module on the same test set, while introducing the traditional machine learning baseline and the information fusion baseline without graph structure as reference. The overall results show that the complete model maintains the best four indicators: Accuracy, Macro-F1, trend consistency rate and governance matching degree, of which Accuracy reaches 93.4%, Macro-F1 reaches 0.917, trend consistency rate is 91.8%, and governance matching degree is 90.6%. Table 5 presents the comprehensive results of the complete model and the main comparison model, and it can be seen that the decline of all indicators is most obvious after removing the relationship modeling, indicating that cross-sectoral structural information has a direct impact on the business environment governance link.

Table 5: Comprehensive performance comparison between the full model and the contrast model

Model	Accuracy / %	Macro-F1	Trend Consistency Rate / %	Governance Matching Degree / %
Full Model	93.4	0.917	91.8	90.6
Without Relationship Modeling	90.7	0.881	88.2	86.9
Without Collaborative Triggering	91.2	0.889	88.9	87.5
Without Strategy Updating	91.6	0.894	89.4	88.1
Temporal Fusion Baseline	89.8	0.867	86.7	84.9

In order to further observe the role of each module in different dimensions, this paper carried out ablation experiments and sorted out the results in Table 6. The results show that the linkage completion rate decreases by 4.8 percentage points after removing the relationship modeling, which indicates that the path structure has an obvious supporting effect on the selection of responsible nodes. After removing the collaborative trigger, the average response time rose to 4.9 h, indicating that the dynamic trigger mechanism had the most direct improvement on timeliness. After removing the strategy update, the closed-loop disposal rate and the responsibility consistency rate both decline, indicating that the feedback correction plays a significant role in stable operation. The ablation results are consistent with the method design in the previous section, and there is no conflict in the improvement direction of indicators.

Table 6: Results of ablation experiments for key modules

Module Configuration	Coordination Completion Rate / %	Average Response Time / h	Closed-Loop Resolution Rate / %	Responsibility Consistency Rate / %
Full Model	90.9	4.2	88.7	91.3
Without Relationship Modeling	86.1	4.8	84.9	87.2
Without Collaborative Triggering	87.4	4.9	85.6	88.1
Without Strategy Updating	88.2	4.6	86.3	88.7

In addition to the overall performance and module contribution, the paper also examines the degree of agreement between the policy output and the actual chain of responsibility. Table 7 presents the governance matching under different event categories. It can be seen that the matching degree of the approval delay category is the highest, 92.1%, followed by the tax refund category, 90.8%, and the appeal aggregation category is slightly lower, 87.6%. This difference shows that the items with more complex text expression still have higher uncertainty in the policy mapping stage, but the system as a whole has been able to maintain a relatively stable matching level. In addition, the standard deviation of the complete model in five repeated experiments is controlled within 0.006, indicating that the system is not sensitive to random initialization and sample segmentation changes. After the paired test of the main indicators, the differences in Accuracy and governance matching between the full model and the best baseline reach a significant level, which makes the results not only have numerical advantages, but also have statistical robustness.

Table 7: Results of governance fit validation for different event categories

Issue Category	Matching Degree / %	Responsibility Consistency Rate / %	Resolution Deviation / %
Approval Delay	92.1	92.4	4.3
Customs Backlog	89.7	90.5	6.1
Tax Return Rejection	90.8	91.2	5.2
Complaint Concentration	87.6	88.9	7.4

From Table 5 to Table 7, it can be seen that the advantages of the complete model are not only reflected in a single identification indicator, but also reflected in three levels of trend judgment, linkage efficiency and governance matching. The relationship modeling improves the identification accuracy of the chain of responsibility, the collaborative trigger mechanism compresses the response delay, and the policy update module enhances the stability of closed-loop disposal. The results show that the dynamic monitoring and collaborative governance model constructed in this paper has a good overall adaptation ability in the business environment scenario of free trade port, and also provides a reliable experimental basis for subsequent system deployment, parameter adjustment and function expansion.

4.5 Discussion

The results show that the dynamic monitoring and collaborative governance system of digital business environment in free trade ports constructed in this paper shows strong stability in the three levels of continuous monitoring, linkage disposal and result matching. The Accuracy of the complete model reaches 93.4%, Macro-F1 is 0.917, and the trend consistency rate reaches 91.8%, which shows that the time series state recognition module can accurately describe the fluctuation, tightening and early warning changes in the business window. Compared with the variant removing relationship modeling, collaborative triggering and policy update modules, the complete model reaches 90.6% in governance matching degree, 90.9% in linkage completion rate, and the average response time is shortened to 4.2 h. It shows that graph relationship propagation, dynamic triggering and feedback update jointly improve the efficiency of responsible node identification and task assignment. Furthermore, the responsibility consistency rate of approval delay items reaches 92.4%, the linkage completion rate of customs clearance backlog items maintains 89.8%, and the coordination performance of tax refund items maintains above 90%, which indicates that the model is not only suitable for links with high degree of structure, but also can maintain a stable governance output in multi-node scenarios. Related results show that after integrating time series recognition, graph calculation and strategy generation into the same information system framework, business environment governance has stronger computability, interpretability and continuous update capabilities. This technology path makes the monitoring results no longer stay in the static evaluation layer, but can directly enter the collaborative governance process, and modify the model parameters and rule thresholds in the way of data writeback, so as to enhance the adaptation ability of the system in the business cycle.

5 Conclusion

Focusing on the task of dynamic monitoring and collaborative governance of the digital business environment in free trade ports, this paper constructs a unified computing framework consisting of multi-source data access, time series status recognition, cross-departmental relationship modeling, risk diagnosis and strategy generation. The experimental results show that the Accuracy of the complete model reaches 93.4%, Macro-F1 is 0.917, trend consistency rate is 91.8%, governance matching degree is 90.6%, linkage completion rate is 90.9%, and the average response time is compressed to 4.2 hours. It shows that the system can accurately identify the change of business status within a continuous business window, and form a more stable cross-departmental linkage output. This method integrates monitoring, coordination and feedback into the same information system link, and makes the business environment governance change from static evaluation to dynamic process that can be calculated, tracked and written back. There are still two limitations in this paper. On the one hand, the data samples mainly come from a single free trade port scenario, and the cross-regional migration ability still needs to be further tested. On the other hand, the appeal text and complex event necklace have higher dispersion in semantic expression, and the current model still has room for expansion in fine-grained interpretation. Future research can continue to introduce cross-region samples, online learning mechanisms, and privacy preserving computing methods, and combine richer semantic representation and causal analysis mechanisms to enhance the generalization ability, robustness, and deployment adaptability of the system in heterogeneous governance scenarios. At the same time, the combination of federated learning, knowledge graph and adaptive threshold update in the government collaboration system can be further studied to improve the recognition ability of the model for continuous concept drift and the overall deployment performance.

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