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The coordinated path of accounting informatization and tax risk control of private enterprises driven by double carbon goals

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SUMMARY: *Facing the needs of fiscal and tax collaborative calculation of private enterprises under double carbon constraints, this paper constructs a coordination analysis framework of accounting informatization and tax risk control, and unifies cleaning, coding and correlation mapping of accounting vouchers, invoice circulation, tax declaration, capital flow, energy consumption records and carbon emission data to form an integrated feature representation of accounting bills, tax and carbon. On this basis, combined with the joint representation learning and rule matching method, the model of accounting informatization state recognition, tax risk classification discrimination and coordination path generation is established, and the check instructions, early warning signals and feedback results are incorporated into the closed-loop processing link. The experiment is carried out based on 4320 groups of private enterprises, and the coordination recognition accuracy is 92.8%, the risk warning accuracy is 91.3%, the F1 value is 91.7%, and the average response delay is 1.8 seconds. In the path execution and dynamic control link, the path execution completion rate maintained at more than 89%, and the state consistency score maintained at more than 80%. The results show that the proposed method can support the collaborative operation of accounting processing, declaration verification and carbon data verification, and is suitable for the fiscal and tax information governance and system deployment in the dual carbon scenario of private enterprises.*

Povzetek: Ob upoštevanju potreb po usklajenih fiskalno-davčnih izračunih zasebnih podjetij v okviru omejitev dvojnega ogljika ta članek vzpostavlja usklajen analitični okvir za informatizacijo računovodstva in nadzor davčnih tveganj. Poskus je bil izveden na podlagi 4320 sklopov vzorcev, pri čemer je natančnost prepoznavanja usklajenosti dosegla 92,8 %, natančnost opozarjanja na tveganja 91,3 %, vrednost F1 91,7 %, povprečna odzivna zakasnitev pa je znašala 1,8 sekunde. V fazi izvajanja poti in dinamičnega nadzora stopnja dokončanja izvajanja poti ostaja nad 89 %, ocena skladnosti stanja pa nad 80 %, kar lahko podpira usklajeno obdelavo računovodskih, davčnih in ogljičnih podatkov ter generiranje izvedbenih poti.

KEYWORDS: *Double carbon target; Accounting informatization; Tax risk control; Multi-source heterogeneous data*

1 Introduction

Under the background of the "double carbon" goal and the promotion of enterprise digital transformation, the accounting business chain, tax-related declaration chain and carbon data collection chain of private enterprises converge. Purchasing, sales, settlement, invoice, energy consumption and emission records precipitate into multi-source heterogeneous data.

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Accounting informatization is also extended from accounting computerization to data collection, rule verification, anomaly identification and risk feedback. The accounting processing, reporting aperture and carbon cost collection of private enterprises rely on unified data interface and intelligent analysis mechanism.

With the deepening application of artificial intelligence, machine learning and automation technology in financial scenarios, accounting information processing and tax identification have presented computational characteristics. Zhang et al. studied the application of explainable artificial intelligence in audit and showed that the model explained service judgment [1]. Achakzai and Juan studied the application of machine learning meta-classifier in financial fraud recognition, and proposed to enhance the discriminative ability of features by ensemble classification [2]. Han et al. studied the combination of blockchain technology and artificial intelligence in accounting audit, and pointed out that shared ledger and intelligent analysis change the framework of financial information processing [3]. Bavaresco et al. studied the automation of accounting services based on machine learning, and proposed that verification tasks can be performed by intelligent systems [4]. Perdana et al. studied the implementation path of robotic process automation in accounting firms and proposed to embed the automated process into the audit business chain [5]. Pargmann et al. studied accounting digitization activities and their capability requirements, and pointed out that accounting processing should turn to the integrated operation of the system by using single-point tools [6]. Ranta et al. studied the application path of machine learning in management accounting and proposed that financial analysis should shift from empirical judgment to data-driven identification [7]. Murorunkwere et al. studied the application of supervised learning in tax fraud prediction and verified the applicability of classification models in tax anomaly identification scenarios [8]. Rabasco and Battiston studied the role of machine learning in predicting the deterrent effect of tax audit, and showed that data modeling can serve tax screening and resource allocation [9].

Existing research provides reference, but the collaborative calculation of accounting informatization and tax risk control of private enterprises under the double carbon constraint still needs to be refined. Accounting data, declaration data and carbon emission data are different in source, granularity and update rhythm. Without unified representation and association mapping, it is difficult to form stable linkage analysis results. In summary, this paper focuses on the coordination path of accounting informationization and tax risk control of private enterprises driven by double carbon goals. The contents are as follows: (1) build a unified representation method for multi-source carbon data of accounting tax; (2) Establish a collaborative discrimination model of accounting informatization status identification and tax risk; (3) The integrated mechanism of coordinated path generation and dynamic feedback is designed, and its effectiveness and adaptability are verified by experiments.

2 Related work

In the research on accounting informatization and tax risk control of private enterprises driven by double carbon goals, the existing results can be roughly divided into three categories:

(1) The intelligent research of accounting information system automatic processing and data coding;

(2) Machine learning research for financial fraud, declaration anomaly and tax recognition;

(3) Research on text computing and data governance for ESG, carbon accounting and sustainable disclosure.

Among them, the first type of research focuses on accounting data collection, voucher identification, coding automation and system interface integration, and the calculation goal focuses on improving processing efficiency and reducing manual errors. The second type of research focuses on fraud identification, abnormal declaration discrimination and tax risk screening, and the computational goal focuses on improving the discriminant power and generalization stability of the model. The third category of research focuses on ESG disclosure, carbon accounting text and sustainable accounting data modeling, with computational goals focused on enhancing the computability and reviewability of non-financial data. The three types of research start from business automation, risk identification and sustainable data governance respectively, and have formed a clear technology spectrum. However, there are still few collaborative modeling results directly oriented to the dual carbon constraint scenarios of private enterprises. This also makes the linkage calculation between accounting informatization, tax risk control and carbon data verification become the current research direction worthy of continuing to promote. Related methods still need to be further integrated and refined linkage output links.

Wang et al. studied multi-modal financial data fraud identification under fine-grained attention, and proposed an attention fusion framework to distinguish heterogeneous information in report fraud [10]. Booker et al. studied the application opportunities of machine learning in accounting information system research, and proposed the AIS meta-theoretical framework to organize the correspondence between supervised learning, unsupervised learning and research design [11]. Bhattacharya and Mickovic studied contextual language learning in financial report texts and proposed to introduce BERT into accounting fraud detection to enhance text semantic discrimination [12]. Zhou et al. studied fraud detection in financial statements in real scenarios, and proposed a data-driven detection process for overall samples and realistic prediction scenarios [13]. Murphy et al. studied the topic modeling of accounting and artificial intelligence literature and proposed a LDA based topological analysis method for accounting AI topics [14]. Zhong and Goel studied the transparent application of explanatory artificial intelligence in audit, and proposed to use XAI to reveal the decision-making basis of the model [15]. Li et al. studied the application of artificial intelligence in ESG forensics, and proposed that AI can be used to extend the link of ESG evidence acquisition and forensic analysis [16]. Zheng et al. systematically sorted out data mining methods in tax risk detection, proposed two types of methods: relational and non-relational, and summarized the combination trend of knowledge-guided and data-driven [17]. Samuel et al. studied carbon accounting in the digital industry and proposed that adaptive decision-making should be used to understand the process of carbon quantification under uncertain conditions [18]. Ferjančič et al. studied the relationship between corporate sustainability report text and ESG score, and proposed to use BERTopic to extract ESG topics and analyze disclosure associations [19]. Koc and Koc studied the classification of account codes in sustainable accounting, and proposed to match bill images and accounting codes by combining deep learning feature extraction and classifier [20].

Although existing research has covered accounting automation, financial anomaly identification, tax detection and carbon disclosure analysis, as shown in Table 1, there is still room for the existing methods in the unified representation of bill tax carbon, cross-source semantic alignment, rule constraint fusion and path generation convergence.

Table 1: Summary of related work.

Reference	Method or Research Object	Data Type	Main Computational Characteristics	Applicability Boundary
[10]	Fine-grained attention-based multimodal financial fraud detection	Financial statements and heterogeneous feature data	Emphasizes cross-modal feature fusion and fine-grained attention modeling	Weak capability in tax rule mapping
[12]	BERT-based accounting fraud text recognition	Financial report text data	Emphasizes contextual semantic representation and linguistic feature learning	Insufficient coverage of coordinated accounting-document computation
[16]	AI-supported ESG assurance analysis	ESG evidence and disclosure data	Emphasizes evidence extraction, assurance analysis, and data association	Limited depth in tax behavior characterization
[17]	Review of data mining methods for tax risk detection	Multi-source fiscal and taxation data	Emphasizes the integration of knowledge guidance and data mining	Insufficient coupling with enterprise accounting states
[20]	Deep learning-driven account code classification	Invoice images and accounting code data	Emphasizes automatic code matching and classification recognition	Narrow scope of carbon data integration

To sum up, this paper focuses on the coordination path of accounting informatization and tax risk control of private enterprises driven by double carbon goals, and the specific research content is as follows:

(1) A unified representation model for multi-source carbon data of billing tax is constructed.

(2) Design the collaborative discrimination mechanism of accounting informatization status identification and tax risk.

(3) The integrated link of coordinated path generation and dynamic feedback is established.

Existing research shows from the technical and application level that multi-modal recognition, text modeling, explanatory artificial intelligence, ESG authentication and tax data mining have formed a strong computing foundation, but the collaborative analysis of accounting, tax and carbon for private enterprises in dual-carbon scenarios still needs to complete feature representation, state recognition, rule matching and closed-loop output within the same framework. Therefore, this paper proposes a coordination framework for accounting informatization and tax risk control for private enterprises, which uses multi-source heterogeneous data modeling, collaborative identification and path generation mechanism to integrate accounting processing chain, declaration verification chain and carbon information verification chain into a unified computing space. The framework not only retains the ability of machine learning to characterize complex patterns, but also retains the ability of business rules to constrain tax billing, reporting and carbon cost collection, which can provide a clear technical basis for subsequent experimental design, performance evaluation and system deployment.

3 Research Methods

3.1 Modeling and feature representation of accounting and tax multi-source data of private enterprises in two-carbon scenario

In the dual-carbon scenario, the multi-source data modeling and feature representation of accounting and tax of private enterprises is not to directly concatenate accounting fields, invoice fields, declaration fields and carbon emission fields, but to establish a joint input structure that can be stably called by subsequent coordination and identification models around the corresponding relationship of account, invoice, tax and carbon information in the business chain. In the process of procurement, production, sales, settlement and declaration, private enterprises will continue to form accounting vouchers, electronic invoices, declaration records, capital flow, energy consumption accounts and emission records. These data have obvious differences in source interface, field granularity, update frequency and semantic caliber. Without a unified mapping, the subsequent recognition results are easily disturbed by redundant fields, time misalignment and caliber offset. Therefore, this paper adopts the modeling process of "multi-source access, standardized processing, time series alignment, difference extraction and joint coding", and organizes the basic data of accounting informatization and tax risk related data into a structured sample in the same computing space.

In order to enable data from different sources to enter subsequent calculations within a unified framework, this paper first defines the original input of a single enterprise sample as a quaternary multi-source set, and its form is written as follows.

$$X_i = \{A_i, F_i, T_i, C_i\} \tag{1}$$

where, A_i represents the accounting data set of the i enterprise sample, including vouchers, books, statements and capital flow; F_i represents the invoice data set. T_i represents the data set of tax declaration and tax processing; C_i represents the set of energy consumption, emission and carbon cost records. The function of Equation (1) is to clarify the multi-source data entry, so that the accounting processing chain, the declaration processing chain and the carbon record chain can be uniformly encapsulated in the same input layer, and provide a clear data boundary for the subsequent feature mapping.

Before multi-source data enters the model, scale unification processing needs to be completed. Accounting amount, tax amount, declaration frequency, unit energy consumption and carbon emission intensity have large differences in numerical ranges, and high-magnitude fields will form unnecessary dominant effects in fusion calculations if dimensional differences are not compressed first. Based on this processing requirement, this paper uses the min-max normalization method to normalize the continuous fields, and the calculation form is written as follows.

$$x'_{ij} = \frac{x_{ij} - \min(x_j)}{\max(x_j) - \min(x_j) + \varepsilon} \tag{2}$$

Here, x_{ij} represents the original value of the i sample on the j field, x'_{ij} represents the normalized result, and ε represents the smoothing term that prevents the denominator from being zero. The function of Equation (2) is to weaken the influence of field dimension differences on the joint representation, so that the subsequent training process can compare the change intensity of different source variables more stably.

After normalization, alignment bias caused by inconsistent time granularity should be solved. Accounting is usually recorded according to the time of business occurrence, invoice circulation has the rhythm of issuing and certification, tax declaration runs according to the declaration cycle, energy consumption and emission data are collected daily, weekly or monthly. If only static field docking is done, it cannot form a stable joint state expression. To this end, this paper introduces the time window mapping mechanism to compress the data from different sources into the same observation window, and its joint state is expressed as follows.

$$S_i^{(t)} = \Phi\left(A_i^{(t)}, F_i^{(t)}, T_i^{(t)}, C_i^{(t)}\right) \tag{3}$$

Here, $S_i^{(t)}$ represents the joint state vector of the i firm in time window t, and $\Phi(\cdot)$ represents the timing alignment operator. The function of Equation (3) is to unify the accounting cycle, billing cycle, declaration cycle and carbon sampling cycle into the same analysis window, so as to reduce the structural disturbance caused by time dislocation.

After the completion of the temporal alignment, the fields from different sources are still in the representation space independent of each other and cannot be directly used for unified recognition. Therefore, this paper further adopts the combination of linear mapping and cross-source fusion to project accounting, invoice, tax and carbon data into the same feature space and form the basic joint representation, whose calculation form is written as follows.

$$R_i = W_a A_i + W_f F_i + W_t T_i + W_c C_i + b \tag{4}$$

Here, W_a, W_f, W_t and W_c represent the mapping matrices of the four types of data respectively, b represents the bias term, and R_i represents the joint representation after the base fusion. The function of Equation (4) is to promote the multi-source business data from the original field layer to the unified representation layer, and provide a common feature base for subsequent difference modeling and coordinated identification.

Base fusion is able to form an overall representation, but it is still insufficient to characterize the local associations between billing differences, reporting deviations, and carbon cost transmission. Considering the direct significance of accounting bill compiling deviation, abnormal tax burden fluctuation, carbon cost collection deviation and abnormal energy consumption per unit output value in coordination analysis, this paper further constructs the difference feature vector to retain these key deviation signals, which is written as:

$$\Delta_i = \left[d_i^{(1)}, d_i^{(2)}, \dots, d_i^{(m)}\right] \tag{5}$$

Here, Δ_i represents the difference feature vector of the i enterprise sample, and $d_i^{(m)}$ represents the m deviation index. The function of Equation (5) is to transform the originally scattered deviation information among accounts, bills, taxes and carbon into a unified difference description structure, so that the model can not only see the overall state, but also see the local changes in the cross-source relationship.

In order to enable the model to dynamically adjust the retention ratio of basic features and deviation signals according to the difference strength, this paper further introduces the gated fusion mechanism to adaptively weight the multi-source features of different enterprise samples. The gated weight calculation form is written as follows.

$$G_i = \sigma(UR_i + V\Delta_i) \tag{6}$$

where $\sigma(\cdot)$ represents the Sigmoid activation function, U and V represent the trainable parameter matrices, and G_i represents the gating weight vector. The function of Equation (6) is to automatically adjust the feature allocation according to the degree of sample difference, so that the model maintains different coding sensitivity between high consistency samples and high deviation samples.

After obtaining the gated weights, the base fusion results and the difference features no longer exist independently, but are organized into a unified final input representation. The joint eigenvector can be further written as follows.

$$Z_i = G_i \odot R_i + (1 - G_i) \odot \Delta_i \tag{7}$$

Here, $\odot$ represents the Hadamard product and Z_i represents the multi-source joint features that are eventually used for subsequent coordinated recognition. The function of Equation (7) is to weighted and recombine the basic fusion results and difference features, so that the final representation retains not only the basic state of accounting informatization, but also the deviation signal related to tax risk and the cost fluctuation information under carbon constraint, so that the subsequent model can perceive the overall structure and local deviation at the same time.

Based on the above processing process, accounting data, bill data, tax data and carbon data no longer exist in the form of decentralized fields, but are organized into a unified structured feature set. From the perspective of method applicability, this modeling method can accept rule fields, continuous variables and time series statistics at the same time, and is easy to access common financial software, electronic tax systems and energy consumption collection terminals of private enterprises. The time window alignment and gated fusion mechanism enable the joint representation to not only have the ability of global integration, but also retain the ability to describe local deviations. The multi-source representation results thus formed can provide a stable input basis for subsequent accounting information state identification, tax risk level discrimination and coordination path generation, and also make the collaborative relationship between accounts, tax and carbon have a clearer calculation expression.

3.2 Construction of coordination and identification model of accounting informatization and tax risk control

Through the joint analysis of the accounting processing status, tax-related declaration status and carbon data collection status of private enterprises, the coordination identification model of accounting informatization and tax risk control aims to identify the coordination level between accounts, bills, taxes and carbon, and output the state results that can be called by the subsequent path generation module. In this paper, the multi-source joint feature representation constructed in the previous section is taken as the input, and combined with collaborative scoring, risk probability estimation, level mapping and rule consistency verification, a coordinated recognition framework covering "state representation-collaborative discrimination-risk identification-level output" is constructed. The model not only emphasizes the recognition accuracy, but also emphasizes the cross-source consistency and result interpretation ability, so as to form a closed loop of accounting and tax collaborative recognition for double carbon scenarios. The model takes account, bill, tax and carbon multi-source data as input, and after joint representation, state mapping, collaborative scoring, risk probability identification and grade discrimination, the interpretable coordination recognition result is formed, and the rule consistency score and feedback signal are output synchronously. The overall structure of the model is shown in Figure 1.

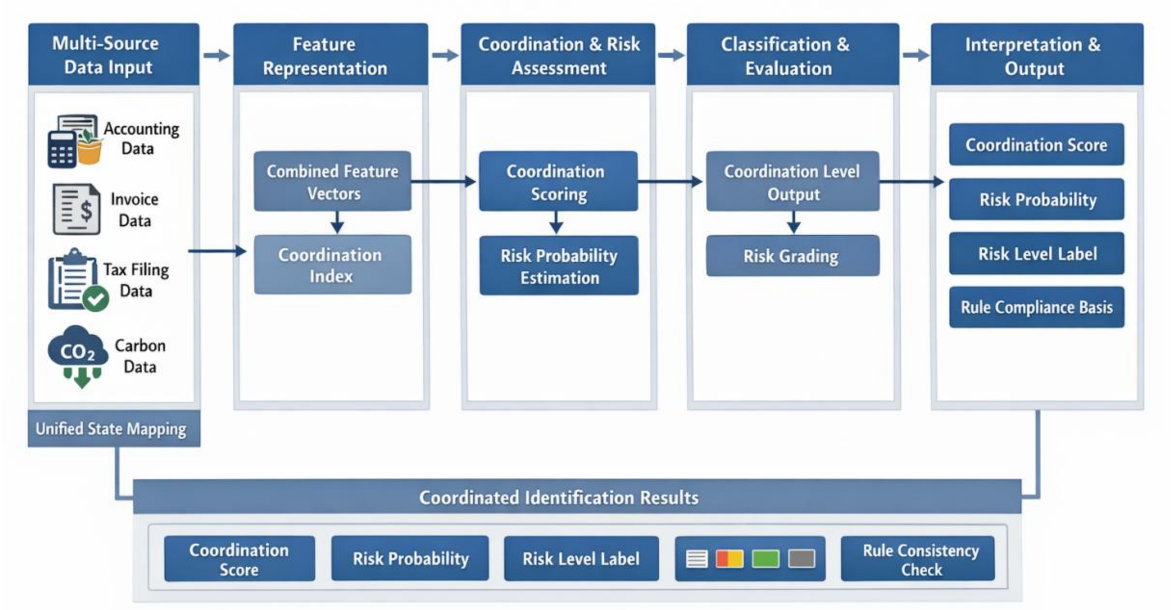

Figure 1: Framework of identification model for coordination of accounting informatization and tax risk control.

As shown in Figure 1, the coordination recognition module does not only output a single classification result, but also retains the coordination score, risk probability, level label and rule basis, so as to provide continuous input for subsequent coordination path generation and dynamic risk control. The construction process of the model is as follows. In the data input stage, the accounting data, invoice circulation data, tax declaration data and carbon collection data are mapped to a unified state space. In the feature representation stage, the joint representation vector and collaborative index were used to construct the accounting-tax state representation. In the collaborative discrimination stage, the accounting informatization collaborative score and tax risk probability were calculated respectively. In the result judgment stage, the coordination level was divided by the joint discriminant score. The output stage is interpreted, and the rule consistency score is combined to generate a reviewable recognition basis.

In order to map multi-source joint features, synergy index and cross-source difference information into the coordinated recognition space at the same time, this paper does not adopt a single linear projection method, but introduces a state mapping structure with residual constraints, so that accounting information, tax information and carbon collection features can be compressed and reconstructed in a unified space. Its state representation is calculated as shown in Equation (8):

$$M_i = LN(\phi(W_z Z_i + W_h H_i + W_\Delta \Delta_i + b_m) + W_r Z_i) \tag{8}$$

Here, M_i represents the coordination identification state vector of the i enterprise sample, Z_i represents the joint feature representation obtained in the previous section, H_i represents the information coordination index, Δ_i represents the difference feature vector between the billing tax carbon, W_z, W_h, W_Δ and W_r represent the trainable mapping matrix, b_m represents the bias term, $\phi(\cdot)$ represents the nonlinear activation function, and so on. $LN(\cdot)$ represents the layer normalization operation. The function of Equation (8) is to map the multi-source input, coordination basis and deviation signals into a unified state space, and retain the stable structure information in the original joint representation through the residual term, so as to improve the continuity and robustness of the recognition representation.

After obtaining the unified state representation, this paper further splits it into accounting informatization subspace and tax risk subspace to characterize the interactive relationship between the two types of states. Accounting information sub-representation and tax risk sub-representation are respectively defined as follows.

$$M_i^a = W_a M_i + b_a, \quad M_i^t = W_t M_i + b_t \tag{9}$$

Here, M_i^a represents the accounting informatization sub-representation of sample i, M_i^t represents the tax risk sub-representation, W_a and W_t represent the corresponding projection matrix, and b_a and b_t represent the bias term. The function of Equation (9) is to split the unified state vector into two identification subspaces with clear business meaning, so that the model does not rely on the overall characteristics when calculating the coordination relationship, but can perceive the internal state of the accounting processing chain and the tax processing chain respectively.

In order to quantitatively depict the coordination degree between the operating state of accounting informatization and the tax processing chain, this paper constructs a bilinear interactive scoring function based on the double subspaces, and its form is shown in Equation (10).

$$c_i = \sigma((M_i^a)^T Q\, M_i^t + \mu^T M_i + b_c) \tag{10}$$

where c_i represents the account-tax coordination score of the i sample, Q represents the bilinear interaction matrix, μ represents the global state weight vector, b_c represents the bias term, and $\sigma(\cdot)$ represents the Sigmoid function. Equation (10) measures the matching degree between accounting informatization state and tax processing state through the double subspace interaction term, and uses the global state term to supplement the overall structure information, so that the coordination score not only reflects the strength of unilateral characteristics, but also reflects the coupling relationship between the two types of states.

In addition to the coordination score, the model also needs to estimate the tax risk intensity synchronously. Considering the obvious compound effect of declaration fluctuation, invoice tax deviation, tax burden anomaly and carbon cost collection deviation, this paper uses gated risk estimation method to calculate tax risk probability, and its form is shown in Equation (11):

$$\begin{aligned} r_i &= \sigma(w_r^T (M_i \odot g_i) + b_r), \\ g_i &= \sigma\big(W_g [M_i^t; \Delta_i] + b_g\big) \end{aligned} \tag{11}$$

Here, r_i represents the probability that sample i is judged as a high tax risk, g_i represents the risk gating vector, w_r represents the risk estimation parameter vector, W_g represents the gating mapping matrix, b_r and b_g represent the bias term, $\odot$ represents the Hadamard product. The function of Equation (11) is to adaptively adjust the retention degree of risk signal according to the tax subspace representation and difference characteristics, so that the model can strengthen the risk-related dimension in the face of high volatility samples and maintain a more stable probability output in the face of low deviation samples.

Considering that accounting informationization coordination status and tax risk probability jointly determine the subsequent path generation results, this paper further constructs a joint discriminant function with carbon constraint correction term to generate a unified coordination identification score. Its form is shown in Equation (12):

$$s_i = \lambda c_i + (1 - \lambda)(1 - r_i) - \rho\, \kappa_i \tag{12}$$

Here, s_i represents the joint coordination score of sample i, λ represents the weight coefficient of coordination score, ρ represents the carbon constraint penalty coefficient, and κ_i represents the carbon collection deviation term, which can be composed of carbon cost deviation per unit output value, emission record integrity deviation and carbon data mapping error. The function of Equation (12) is to incorporate accounting informationization coordination state, tax risk intensity and carbon collection stability under double carbon constraint into the same evaluation scale, so that the joint score is more in line with the goal of "collaborative identification of accounting bill, tax and carbon" in this scenario.

The collaborative recognition part is optimized by binary cross entropy, and its calculation form is shown in Equation (13).

$$L_c = -\frac{1}{N}\sum_{i=1}^{N}[\widehat{y_i^c}\log(c_i) + (1-\widehat{y_i^c})\log(1-c_i)] \tag{13}$$

Here, N represents the number of training samples and $\widehat{y_i^c}$ represents the collaborative state label of sample i. The function of Equation (13) is to measure the deviation between the collaborative scoring output and the true state label, and to push the model to learn the stable boundary of the bill-tax-carbon collaborative relationship.

In the tax risk identification part, the cross-entropy loss with class weight is used to enhance the identification ability of the model for a few high-risk samples. Its calculation form is shown in Equation (14):

$$L_r = -\frac{1}{N}\sum_{i=1}^{N}[\omega_1\widehat{y_i^r}\log(r_i) + \omega_0(1-\widehat{y_i^r})\log(1-r_i)] \tag{14}$$

Here, $\widehat{y_i^r}$ represents the tax risk label of sample i, and ω_1 and ω_0 represent the weights of the high-risk and non-high-risk classes, respectively. The function of Equation (14) is to alleviate the influence of the unbalanced distribution of tax risk samples on the training process, so that the model can maintain higher sensitivity in high risk identification.

In the decision stage, in order to map the continuous joint discrimination scores into discrete coordination levels, three discrimination thresholds are set and a four-level rank mapping function is constructed. Its form is shown in Equation (15):

$$y_i = \begin{cases} 0, & s_i < \tau_1 \\ 1, & \tau_1 \le s_i < \tau_2 \\ 2, & \tau_2 \le s_i < \tau_3 \\ 3, & s_i \ge \tau_3 \end{cases} \tag{15}$$

Here, y_i represents the Coordination identification result of the i sample, 0 represents the Risk-Conflict State, 1 represents Weak Coordination, 2 represents Moderate Coordination, 3 represents High Coordination, and 1 represents weak coordination. τ_1, τ_2, and τ_3 denote the rank division thresholds. The function of Equation (15) is to transform the continuous joint score into four-level discrete states, so that the coordination recognition result can be consistent with the level output in the figure, the path scheduling priority and the subsequent dynamic control strategy.

In order to enhance the review basis of the output results, this paper further introduces the rule consistency score to quantify the degree of agreement between the model results and the accounting bill compiling rules, the tax burden interval rules, the declaration cycle rules and the carbon collection rules. Its calculation form is shown in Equation (16):

$$u_i = \frac{\sum_{k=1}^{K} \gamma_k g_{ik}}{\sum_{k=1}^{K} \gamma_k} \tag{16}$$

Here, u_i represents the rule consistency score of sample i, g_{ik} represents the hit result of the k rule on sample i, γ_k represents the rule weight, and K represents the total number of rules. The function of Equation (16) is to supplement the rule basis for model discrimination, so that the coordination identification results have a clearer interpretation path in the business review and system deployment scenarios.

In summary, the coordinated identification model of accounting informatization and tax risk control can complete state mapping, collaborative scoring, risk probability estimation, level output and rule verification on the basis of multi-source joint representation. The model output can not only reflect the operation state of enterprise accounting informatization, but also depict the tax risk intensity and its coupling relationship with carbon collection link, which provides stable input for the integrated design of coordinated path generation mechanism and dynamic risk control in the next section.

3.3 Integrated design of coordinated path generation mechanism and dynamic risk control

Accounting informatization and tax risk control of private enterprises have the characteristics of cross-source linkage and periodic update. It is difficult to support continuous fiscal and tax collaborative processing under double carbon constraints based on only a single identification result. In order to enhance the executability of the output in the previous section, this paper introduces an integrated mechanism of coordinated path generation and dynamic risk management and control, and organizes the "state identification-path matching-rule execution-effect feedback-model update" into a closed-loop operation framework. The mechanism consists of three core submodules, as shown in Table 2.

Table 2: Coordination path generation and dynamic control integration framework.

Submodule	Main Input	Core Processing Logic	Main Output
Path Generation	Coordination level, risk probability, rule score, enterprise attributes	Combines rule base and similar-sample retrieval, with carbon constraints superimposed to filter actions	Path ID, priority, action set
Dynamic Control	Path actions, accounting-invoice-tax-carbon state vector, interface logs	Executes declaration verification, invoice-account reconciliation, tax burden monitoring, and carbon cost aggregation scheduling	Control result, execution flag
Feedback Iteration	Correction results, subsequent declaration status, rule hit conditions	Updates samples, threshold parameters, and rule weights	Sample set, rule base, model parameters

According to the joint score, risk probability and rule consistency score, the system divides the enterprise sample into three levels of coordinated stability, coordinated fluctuation and coordinated deviation, and calls different path sets. Coordinate stable samples to maintain the stability of processing and declaration; The coordinated fluctuation samples mainly control the deviation accumulation and improve the check frequency. The coordinated deviation samples are given priority to enter the key review and risk blocking links. The control objectives and typical actions corresponding to different levels are shown in Table 3.

Table 3: Path goals versus typical actions for different coordination levels.

Coordination Level	Judgment Basis	Main Control Objective	Typical Actions
Stable Coordination	High joint score, low risk probability, and good rule consistency	Maintain stability in processing and declaration	Routine verification, periodic reconciliation of invoice-account mappings, and tracking the completeness of carbon aggregation
Fluctuating Coordination	Medium joint score with partial field deviations	Control the accumulation of deviations	Increase verification frequency, trigger invoice-tax rechecks, and supplement missing carbon data
Deviated Coordination	Low joint score or continuously high risk probability	Block the spread of abnormalities	Initiate key rechecks, freeze high-risk declaration links, and re-aggregate carbon costs

In order to make the path output have a unified quantitative basis, this paper defines the path matching score function, whose form is shown in Equation (17) :

$$p_i = \eta_1 y_i + \eta_2(1 - r_i) + \eta_3 u_i + \eta_4 \mathrm{sim}(M_i, \bar{M}_j) \tag{17}$$

where p_i represents the path matching score, y_i represents the coordination level mapping value, r_i represents the tax risk probability, u_i represents the rule consistency score, and $\mathrm{sim}(M_i, \bar{M}_j)$ represents the similarity between the current sample and the prototype state of the path library. The function of Equation (17) is to unify the recognition results, rule information and historical samples into the same scoring space, which is used to screen the most suitable coordination path for the current state.

After obtaining the path score, the system also needs to determine the specific execution plan from the set of candidate actions. To this end, this paper constructs an action selection function, whose form is shown in Equation (18):

$$a_i = \arg\max_{k \in \Omega_i}(\omega_k p_i + \delta_k q_i - \rho_k c_i^*) \tag{18}$$

where a_i represents the final selected action plan, Ω_i represents the set of executable actions, q_i represents the interface execution feasibility score, c_i^* represents the action execution cost, ω_k, δ_k and ρ_k represent the adjustment coefficients of path response, feasibility and cost respectively. The function of Equation (18) is to screen out the most appropriate set of control instructions in the current state from a variety of alternatives.

After the path execution is completed, the system flows the control results back to the model update link. To this end, this paper defines the feedback update function, whose form is shown in Equation (19):

$$\theta^{(t+1)} = \theta^{(t)} + \mu\left(e_i^{(t)} + \xi_i^{(t)} - \zeta_i^{(t)}\right) \tag{19}$$

where $\theta^{(t+1)}$ represents the joint model and rule parameters at time t, $e_i^{(t)}$ represents the state correction after path execution, $\xi_i^{(t)}$ represents the rule hit correction, $\zeta_i^{(t)}$ represents the new deviation penalty term, μ represents the update step. The function of Equation (19) is to update the model parameters and rule weights synchronously according to the execution results, so that the system can maintain its adaptability to new states in subsequent cycles.

The above mechanism indicates that this paper adopts the design idea of "recognition result driven, rule base constraint, feedback chain reflux". The model in the previous section outputs coordination level and risk probability, while in this section, the identification results are further transformed into path actions, execution results and iterative update signals, so that the accounting information state, tax risk intensity and carbon collection constraint enter the dynamic scheduling process together, which provides a computable basis for subsequent path effectiveness analysis and feedback response evaluation.

4 Experimental Design

The data set used in this study is composed of accounting processing data of private enterprises, invoice circulation data, tax declaration data, capital flow data, energy consumption and carbon emission records. The total number of samples is 4320 groups, covering four typical industries such as manufacturing, commerce, logistics and comprehensive services. The samples are sorted according to the continuous operation cycle of the enterprise, and each group of data includes accounting status, bill status, declaration status, carbon collection status and risk marker information, which is suitable for accounting information status identification, tax risk discrimination and coordination path generation tasks. In order to ensure the training consistency, this paper divided the training set, validation set and test set according to 7:2:1, and interpolated the missing fields, normalized the continuous variables, and coded the category fields. The experimental environment is deployed on a high-performance workstation with hardware configuration including Intel Xeon Gold 6330 processor, NVIDIA RTX A6000 graphics card, 128 GB memory and 2 TB SSD. The software environment is Ubuntu 22.04, Python 3.10, PyTorch 2.1, scikit-learn 1.3, and Pandas, NumPy, and Matplotlib are used for data processing, statistical analysis, and visualization of results. In this paper, GCN-Attention, BiLSTM-Rule and XGBoost-Threshold are selected as comparison models. GCN-Attention is used to verify the graph structure modeling ability, and BiLSTM-Rule is used to compare the timing and rule fusion effect. XGBoost-Threshold is used to compare the performance of tree models in hierarchical recognition tasks. The parameter Settings were tuned on the unified validation set to ensure a fair comparison of different models under the same data conditions. In the training process, the batch size is set to 64, the initial value of the learning rate is set to 0.001, the training rounds are set to 120, and the early stopping strategy is used to suppress overfitting. Coordination identification and path output are completed in the same test process to ensure that the experimental link is consistent with the actual deployment link.

5 Analysis of experimental results

5.1 Analysis of coordinated identification accuracy and risk early warning performance

This experiment analyzed the coordination recognition accuracy and risk early warning performance, which was used to test the model's ability to describe the coordination state of accounting, tax and carbon and distinguish the high-risk samples. In order to ensure the consistency of the comparison results, this paper compares the method proposed in this paper with GCN-Attention, BiLSTM-Rule, and XGBoost-Threshold under a unified data division and evaluation diameter, and the evaluation indicators are selected to coordinate recognition accuracy, early warning accuracy, F1 value, AUC and average response delay.

As shown in Figure 2, the proposed method keeps leading in all recognition indicators. The coordination recognition accuracy is 92.8%, which is higher than 89.6% of GCN-Attention, 88.4% of BiLSTM-Rule and 90.7% of XGBoost-Threshold. The early warning accuracy reaches 91.3%, which indicates that the multi-source joint representation and collaborative discrimination mechanism can more effectively distinguish real anomalies from local fluctuations. The F1 value reaches 91.7%, indicating that the model maintains a good balance between recall ability and false alarm control. The AUC reaches 0.941, indicating that the model has high discrimination under different discrimination thresholds. The average response delay is controlled within 1.8 seconds, which also shows that the model can meet the continuous call requirements in the fiscal and tax information governance scenario.

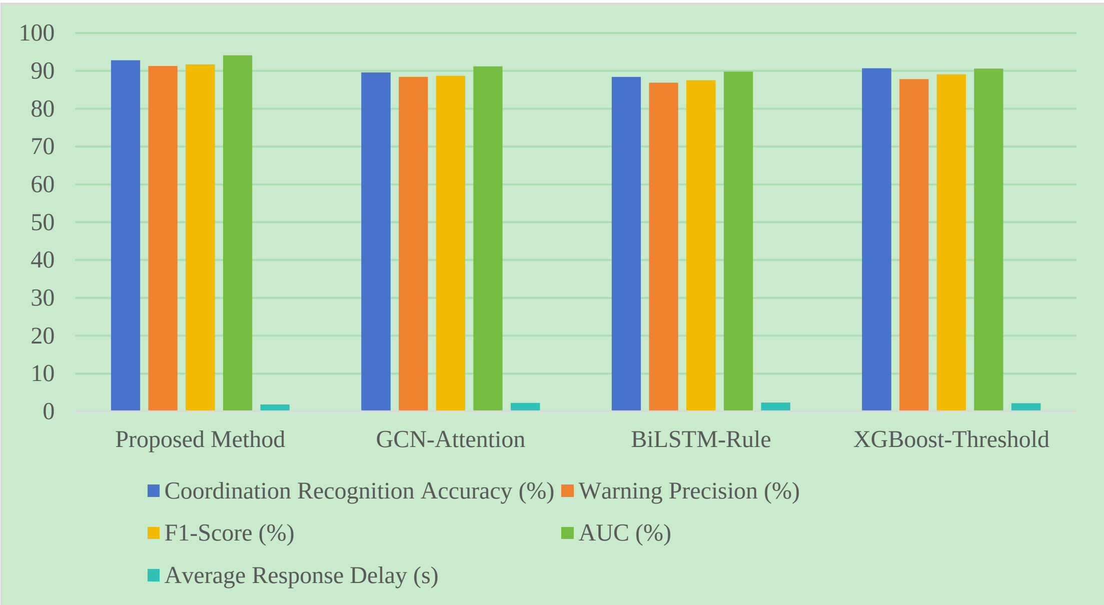

Figure 2: Comparison of coordinated identification and early warning indicators for different models.

As shown in Figure 3, under the condition that the proportion of disturbances continues to increase, the F1 values of each model show a significant decrease, but the decrease amplitude and decay rhythm are quite different. The proposed method decreases from 91.7 to 76.8, although it also decreases in the high disturbance interval, it still maintains the highest recognition level as a whole, indicating that the multi-source joint representation and rule consistency constraint have a strong buffer effect on cross-source migration and abnormal miss. GCN-Attention decreases from 88.7 to 42.6 with the largest decrease, indicating that the model is sensitive to high perturbation conditions. BiLSTM-Rule decreased from 87.5 to 53.4, with continuous attenuation in the middle and later segments. The XGBoost-Threshold decreased from 89.1 to 57.3, which maintained a certain stability in the early stage, but the decline of recognition ability accelerated after 15%. On the whole, the proposed method can still maintain a high discrimination margin and output stability under the condition of disturbance enhancement.

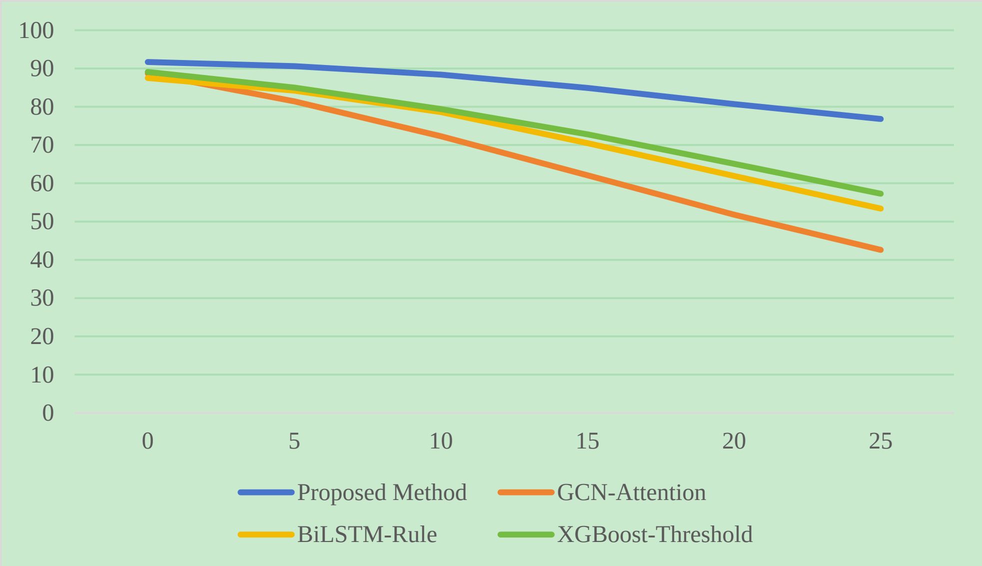

Figure 3: F1 value variation of each model under disturbance condition.

To further verify the reliability of the results, this paper carried out 10 repeated experiments under the same configuration, and counted the mean, standard deviation and 95% confidence interval of the indicators, and the results are shown in Table 4.

Table 4: Statistics of coordinated identification and risk warning results.

Metric	Proposed Method (Mean ± Standard Deviation)	95% Confidence Interval	Best Comparative Model (Mean ± Standard Deviation)
Coordination Recognition Accuracy	0.928 ± 0.006	[0.916, 0.939]	0.907 ± 0.010 (XGBoost-Threshold)
Warning Precision	0.913 ± 0.007	[0.899, 0.926]	0.884 ± 0.011 (GCN-Attention)
F1-Score	0.917 ± 0.006	[0.905, 0.929]	0.891 ± 0.010 (XGBoost-Threshold)
AUC	0.941 ± 0.005	[0.931, 0.950]	0.912 ± 0.009 (GCN-Attention)
Average Response Delay (s)	1.80 ± 0.04	[1.72, 1.88]	2.14 ± 0.06 (XGBoost-Threshold)

Table 4 shows that the standard deviation of each index of the proposed method in 10 repeated experiments is controlled within a small range, and the 95% confidence interval is concentrated and the cross range is limited, indicating that the model output is not sensitive to random initialization, sample division and disturbance injection. Combining Figure 2 and Figure 3, it can be seen that the coordinated recognition mechanism constructed in this paper not only maintains a high recognition level in the static evaluation index, but also maintains a stable discrimination boundary and response efficiency when the external disturbance is gradually enhanced. This shows that the multi-source joint representation, the collaborative discriminant function and the rule consistency constraint form an effective cooperation, so that the model can output reviewable recognition results when there are offsets, omissive and fluctuations in the carbon information of the accounting tax, and provide reliable input for the subsequent coordination path generation and dynamic control.

5.2 Dynamic control effect and effectiveness analysis of coordination path

After completing the coordination identification and risk early warning experiment, this paper further analyzes the effect of dynamic control and the effectiveness of coordination path, focusing on the state convergence ability, rule response performance and execution link stability after path execution. In order to ensure the consistency of the results, this paper evaluates the path execution completion rate, exception resolution rate, state consistency score and average feedback delay under unified data division, unified threshold setting and unified execution cycle. The dynamic control results of the proposed method on the three datasets are shown in Figure 4.

Figure 4: Comparison of dynamic control effect and path execution metrics.

As shown in Figure 4, the path execution completion rate of the proposed method on the three sets of data of UCI-BP, Kaggle-BP and Kaggle-CCR is 93%, 91% and 89%, the abnormal drop rate is 37%, 35% and 33%, and the state consistency score is 84%, 82% and 80%, respectively. The average feedback delay is 1.95 seconds, 2.03 seconds and 2.11 seconds, respectively. The results show that the action set output by the model can more accurately act on the link of bill check, declaration recheck and carbon collection correction, and maintain a relatively stable linkage structure of bill tax and carbon after execution. The path execution completion rate of the three groups of data maintained at a high level, indicating that the coordinated path generation mechanism had good executability. The abnormal drop rate maintained a continuous decline feature, indicating that the dynamic control process could effectively converge to the deviated state. The state consistency score is always maintained above 80%, which also indicates that the multi-source information linkage relationship is relatively stable after path execution. The average feedback delay is controlled within 2.11 seconds, which indicates that the dynamic control module enhances the closed-loop processing without bringing obvious execution burden, and can meet the requirements of subsequent continuous invocation and system deployment.

In order to further investigate the stability of the dynamic management and control link under different disturbance conditions, this paper continues to compare the state consistency changes of each model when the disturbance proportion gradually increases, and the results are shown in Figure 5.

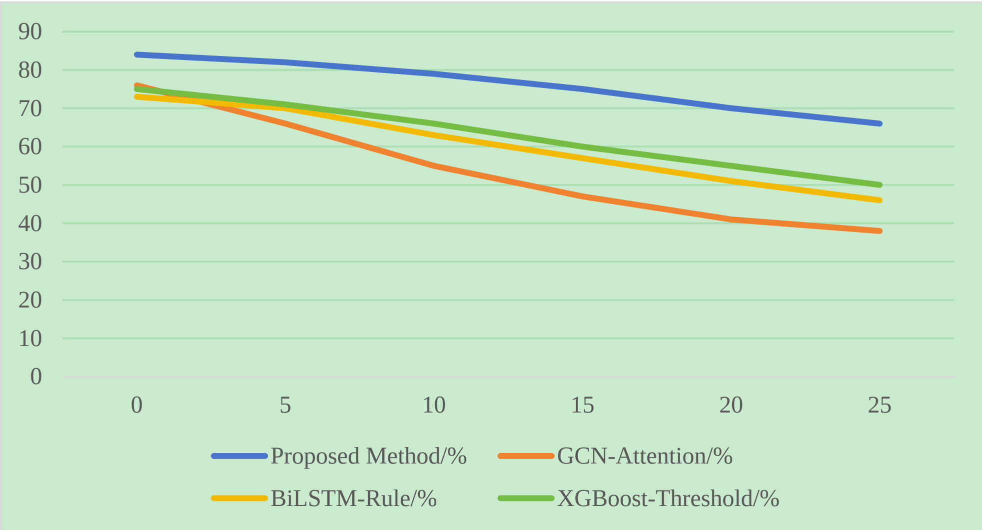

Figure 5: State consistency changes under disturbance conditions.

As shown in Figure 5, as the proportion of disturbances continues to increase, the state consistency scores of all models show a decrease, but the decrease magnitude is obviously different. The proposed method maintains 84%, 82%, 79%, 75%, 70% and 66% in the six disturbance stages of 0%, 5%, 10%, 15%, 20% and 25%, respectively, and the overall decline process is relatively stable. In contrast, GCN-Attention has the largest attenuation from 76% to 38%. BiLSTM-Rule decreased from 73% to 46%, and decreased rapidly in the middle and posterior segments. The XGBoost-Threshold decreases from 75% to 50%, and although it maintains a certain stability in the front segment, it also shows a significant attenuation in the high disturbance interval. The results show that after multi-source joint representation, coordination discriminant function and rule consistency check work together, the proposed method can still maintain strong path executability and control continuity under the condition of accounting bill mapping offset, declaration field missing and carbon collection error increase.

In order to further analyze the contribution of each component module to the overall performance, this paper sets up ablation experiments and arranges the results as shown in Table 6. By comparing the difference between the complete model and the deleted module, the dependence of the dynamic control effect on the three parts of difference feature coding, rule consistency check and dynamic feedback update can be more clearly observed.

Table 6: Results of ablation experiments.

Model Configuration	Path Execution Completion Rate (%)	Abnormality Recovery Rate (%)	State Consistency Score (%)	Average Feedback Delay (s)

Full Model	93	37	84	1.95
Without Differential Feature Encoding	87	30	76	2.11
Without Rule Consistency Verification	86	29	74	2.28
Without Dynamic Feedback Updating	85	27	73	2.19

It can be seen from Table 6 that after removing the differential feature coding module, the path execution completion rate drops to 87%, the abnormal drop rate drops to 30%, and the state consistency score drops to 76%, indicating that the cross-source deviation signal has a direct support role in the path selection stage. After removing the rule consistency check, the average feedback delay increases to 2.28 seconds, and the state consistency score decreases to 74%, which indicates that the rule basis not only assumes the function of result interpretation, but also participates in the screening and convergence process of control actions. After removing the dynamic feedback update, the abnormal drop rate is reduced to 27%, and the path execution completion rate is reduced to 85%, which indicates that the control chain in the subsequent cycle will have a weakened response if the model lacks the return flow of execution results and parameter correction. The complete model achieves the best results on the four indicators, indicating that the dynamic control effect is not determined by a single module, but depends on the continuous cooperation between multi-source modeling, collaborative recognition, rule constraints and feedback update.

It can be seen from Figure 4, Figure 5 and Table 6 that the proposed method is superior to the comparison models in terms of path execution efficiency, abnormal convergence ability and feedback stability, which also indicates that the constructed mechanism can provide more reliable computational support for the fiscal and tax collaborative governance of private enterprises in the dual-carbon scenario. At the same time, the results of the proposed method on the three types of data sets remain consistent, indicating that the path generation module has a good adaptation ability to industry differences and sample fluctuations, and the transfer relationship between the execution results and the recognition output is relatively stable, which also forms a continuous confirmation with the accuracy analysis in the previous section.

6 Discussion

Based on the above experimental results, the collaborative model of accounting informatization and tax risk control constructed in this paper shows strong stability in both recognition and execution levels. The coordinated recognition accuracy is 92.8%, the early warning accuracy is 91.3%, the F1 value is 91.7%, and the average response time delay is controlled within 1.8 seconds, which indicates that the multi-source joint representation and collaborative discrimination mechanism can better support the identification of carbon status of tax accounts. In the dynamic control link, the path execution completion rate of the three groups of data is 93%, 91% and 89%, the abnormal resolution rate is 37%, 35% and 33%, the state consistency score is 84%, 82% and 80%, and the average feedback delay is maintained at 1.95 seconds, 2.03 seconds and 2.11 seconds. It shows that the recognition results can be stably transmitted to the path generation and feedback update link. From the perspective of mechanism, the advantage of the model comes from the continuous cooperation of differential feature coding, rule consistency check and dynamic feedback update, rather than the local gain of a single module. In the ablation results, the path execution completion rate is reduced to 87% after removing the differential feature coding, the state consistency score is reduced to 74% after removing the rule consistency check, and the anomaly resolution rate is reduced to 27% after removing the dynamic feedback update, which further indicates that multi-source modeling, rule constraints and feedback reflux jointly determine the system effect. The framework can be further embedded into financial sharing platforms, e-tax interfaces and carbon data collection terminals to achieve continuous computing and reviewable deployment. At the same time, the state consistency scores of 84%, 82% and 80% show that the multi-source data still maintain good structural consistency after path execution, and there is no obvious linkage imbalance, indicating that the system operation has strong stability.

7 Conclusions

Focusing on the collaborative needs of accounting informatization and tax risk control of private enterprises driven by double carbon goals, this paper constructs a computing framework for multi-source data of accounts, receipts, taxes and carbon. Starting from the multi-source data modeling, the unified representation of accounting vouchers, invoice circulation, tax declaration, capital flow, energy consumption records and carbon emission information is carried out. On this basis, the collaborative discrimination model of accounting information status recognition and tax risk is established, and the integration mechanism of coordination path generation and dynamic feedback is further designed. The recognition result, rule basis and execution action can be transmitted in the same link. The framework integrates accounting processing chain, tax declaration chain and carbon collection chain into the unified computing space, enhances the structural integrity of fiscal and tax collaborative analysis, and provides a deployable technical path for private enterprises to digital fiscal and tax governance.

At the same time, this paper still has some limitations. The sample sources mainly focus on the existing enterprise data scenarios, and there is still room for expansion of the industry span and regional coverage. The adaptation ability of the model to cross-regional caliber differences, system adjustments and interface changes needs to be further verified. The construction of the rule base is currently based on the existing business logic. In the face of new declaration modes, complex bill circulation relationships and higher frequency carbon data collection scenarios, a finer dynamic update mechanism is still needed. Further research can be carried out in three directions. First, cross-industry and cross-region samples can be expanded to enhance the migration ability of the model in complex scenarios. Secondly, incremental learning, multi-modal text information and online rule update mechanism are introduced to improve the system's responsiveness to policy changes and business fluctuations. Thirdly, the embedded verification is carried out by combining the financial sharing platform, electronic tax interface and carbon data collection terminal, so that the coordination identification, path generation and feedback update form a more stable closed-loop operation in the real business process.

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