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Graph neural network modeling digital economy industrial ecology and artificial intelligence collaborative development mechanism

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SUMMARY: *In order to reveal the internal logic of the co-evolution of digital economy industrial ecology and artificial intelligence, an analysis framework of the co-development mechanism driven by graph neural network was constructed. Starting from the enterprise, platform, technology supply and regional unit, this paper designed a heterogeneous collaborative network structure, established the linkage mechanism of hierarchical representation learning, ecological perception and intelligent decision-making, and carried out effect test combined with multi-regional samples. The results show that the model performs better in collaborative identification and optimal configuration, with the Accuracy reaching 91.7%, Macro-F1 reaching 90.3%, and AUC reaching 93.6%. The collaborative efficiency of typical areas, the degree of cross-subject interaction and the matching rate of artificial intelligence are improved. The research shows that graph neural network can effectively depict multi-agent association, cross-layer propagation and regional differences in the industrial ecology of digital economy.*

KEYWORDS: *Digital economy; Industrial ecology; Graph neural network; Mechanism of coordinated development*

1 Introduction

With the continuous deepening of the digital economy, the industrial operation mode has changed from a relatively stable linear organization to a networked ecological structure driven by data, platform connection and intelligent evolution in parallel. Traditional industrial analysis methods are mostly based on a single industry, a single indicator or static relationship. Although they can describe local changes, it is difficult to reveal the linkage process between digital infrastructure, platform enterprises, innovation agents, algorithmic capabilities and institutional environment. Problems such as insufficient relationship description, lag of dynamic response and coarsening of mechanism identification often occur [1]. At the same time, artificial intelligence technology is accelerating from the tool level into the key links of production organization, resource allocation, knowledge diffusion and decision support, promoting the digital economy from factor aggregation to structural remodeling. Due to its ability to simultaneously learn node attributes, edge relationships and topological propagation characteristics in complex associated data, graph neural networks have become an important computational means for characterizing the interaction of heterogeneous agents, identifying multi-layer network dependencies and revealing evolution mechanisms [2-4]. However, existing research still mostly stays at the level of technology application or concept discussion,

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and there is still a lack of a unified graph modeling framework for the collaborative development mechanism of digital economy industrial ecology and artificial intelligence, especially in cross-industry, cross-region and multi-agent coupling scenarios, the collaborative path, conduction logic and boundary constraints still need to be further clarified [5].

Based on this, this paper intends to construct a graph neural network modeling method for the collaborative development mechanism of industrial ecology and artificial intelligence in digital economy, so as to improve the recognition ability of industrial correlation structure, collaborative diffusion path and intelligent decision-making process. The core goal of this research is to map the enterprises, platforms, technologies, capital and regional units in the industrial ecology into a computable graph structure, and combine hierarchical representation learning and collaborative decision-making mechanism to describe the ecological evolution law under the participation of artificial intelligence. Aiming at this goal, this paper focuses on three questions: first, how to build a collaborative network with both structural expression and realistic interpretation power according to the multi-agent interaction characteristics of digital economy industrial ecology; Secondly, how to design a graph neural network model that ADAPTS to the characteristics of heterogeneous nodes, multiple relationships and hierarchical propagation, so as to realize the effective representation and prediction of collaborative states. Thirdly, how to form an artificial intelligence collaborative decision-making mechanism on the basis of industrial ecological perception, so as to improve the efficiency of industrial resource allocation and system operation resilience.

The paper is divided into six parts. The first part is the introduction, which explains the research background, goal and problem definition. The second part is a literature review, combing the relevant research on industrial ecology of digital economy, collaborative development of artificial intelligence and graph neural network modeling. The third part is the method part, which constructs the collaborative network structure, the hierarchical graph neural network model and the collaborative decision-making mechanism. The fourth part is effect analysis, which examines the performance of the model and its performance at industry level, regional level and abnormal circumstances. Section 5 opens the discussion; Section 6 concludes the paper and proposes future research directions.

2 Literature Review

In recent years, the research on industrial ecology of digital economy has gradually shifted from static investigation of industrial scale, innovation output and policy environment to comprehensive analysis of network relationship, collaborative structure and evolution mechanism. Existing literature points out that digital platform, data elements, technical infrastructure and institutional support are not isolated variables, but are jointly embedded in the industrial ecology, forming a multi-layer interactive structure by connecting enterprises, capital, technology and market [6-8]. Roundy et al. believe that entrepreneurial ecosystem has obvious complex adaptability, and its operation process is jointly affected by inter-subject dependence, resource circulation path and local governance structure [9, 10]. Baldwin et al. further proposed that innovation research should extend the perspective of ecosystem from single-agent competition to collaborative value creation to explain the nonlinear characteristics of technology diffusion and industrial linkage [11]. This shows that the key to the industrial ecology of digital economy is not only the strength of a certain subject, but also whether a stable, efficient and sustainable collaborative network can be formed between different nodes.

The research on the coordinated development of artificial intelligence and industrial ecology has gradually moved from the level of technology application to the level of mechanism explanation. Most of the existing achievements are carried out from the directions of artificial intelligence innovation environment, enterprise niche, intelligent decision embedding and organizational collaboration reconstruction. Roundy and Asllani pointed out that artificial intelligence is changing the way of knowledge generation, the logic of opportunity identification and the efficiency of resource matching in the entrepreneurial ecosystem, making the industrial system show stronger characteristics of algorithm intervention [12]. Nam et al. conducted a survey based on South Korean AI startups and found that the AI industry ecology not only depends on technology supply ability, but also is significantly affected by data acquisition, platform access and cooperation network density [13]. Krause et al., starting from the context of Industry 5.0, discussed the problem of knowledge graph support in human-machine collaborative governance, emphasizing that intelligent systems should serve cross-agent collaboration instead of staying at the local automation level [14]. Related research provides important inspiration for understanding how artificial intelligence participates in the industrial ecology of digital economy. However, many analyses still focus on concept induction, and the description of collaborative transmission path, structural hierarchy difference and dynamic decision-making feedback is still insufficient.

At the method level, graph neural networks have been widely used in complex network relationship modeling, link prediction, and node representation learning due to their ability to handle non-Euclidean data structures. Kosasih and Brintrup used graph neural network to predict the implicit association in the supply chain, and proved that its structure mining ability in complex business networks was significantly better than traditional machine learning methods [15]. Kosasih et al. then combined knowledge graph reasoning with graph neural network for supply chain risk management, further improving the expression ability of heterogeneous relationships [16]. Longa et al. pointed out in the research review of temporal graphs that graph neural networks have gradually acquired the ability to deal with dynamic graphs, multi-relational graphs and spatio-temporal propagation processes, which provides a methodological basis for the study of industrial ecological evolution [17]. Basole et al. applied visual analysis driven by artificial intelligence to complex business ecological intelligence recognition, which also shows that graph structure learning and industrial system analysis have strong adaptability [18]. However, the existing researches on graph neural networks focus more on scenarios such as supply chain, traffic flow and recommendation systems, and the overall modeling of the collaborative development of digital economy industry ecology and artificial intelligence is still limited, especially the lack of a unified framework that integrates regional level, industry level and intelligent decision-making process.

Based on the existing research, it can be found that some progress has been made in the ecological interpretation of digital economy, artificial intelligence collaborative logic and graph model methods, but there are still three shortcomings. First, the research on industrial ecology of digital economy is mainly based on conceptual framework or local relationship recognition, and there is a lack of a unified network representation that can simultaneously contain enterprises, platforms, technologies and regional units. Second, the discussions on the collaborative development of artificial intelligence pay more attention to the technology empowerment effect, and insufficiently reveal the propagation path and heterogeneous influence of the collaborative mechanism at different levels. Third, although the existing graph neural network applications have strong structure learning ability, they have not yet formed a closed-loop modeling system connected with "ecological perception, relationship propagation, collaborative decision making, feedback optimization". In order to more clearly present the focus and application boundaries of existing research, this paper makes an inductive comparison of representative literatures, as shown in Table 1.

Table 1: Comparison of related studies on collaborative development of digital economy industrial ecology and artificial intelligence

References	Research Method	Application Context	Focus	Limitations
Kosasih et al. [1]	Knowledge graph reasoning and graph neural networks	Supply chain risk management	Heterogeneous relationship reasoning and risk identification	Oriented toward the supply chain context, with insufficient extension to industrial ecology
Longa et al. [2]	Review of temporal graph neural networks	Dynamic graph learning	Time-varying relationship modeling and open problem analysis	Focuses mainly on method summarization and lacks an industrial empirical framework
Nagy et al. [4]	Knowledge graph framework	Collaborative manufacturing	Human–machine collaboration and knowledge organization	Insufficient discussion of regional and industrial hierarchical differences
Krause et al. [5]	Knowledge graph and collaborative governance analysis	Industry 5.0	Human–machine collaborative management and governance challenges	Emphasizes governance discussion and lacks quantitative modeling
Roundy et al. [11]	Literature review and content analysis	AI innovation ecosystem	AI innovation contexts and ecosystem structure	Strong in interpretation but limited in predictive capability
Nam et al. [12]	Survey analysis	AI entrepreneurial ecosystem	Data, platforms, and cooperation networks	Insufficient characterization of regional diffusion and dynamic transmission

Table 1 shows that although the existing research provides theoretical basis and method reference for this paper, there are still obvious gaps in unified network modeling, hierarchical collaborative identification and closed-loop decision mechanism. Based on this, this paper introduces graph neural network to hierarchical model the multi-agent relationship in the industrial ecology of digital economy, and on this basis, discusses the action mechanism and effect difference of artificial intelligence in collaborative development.

3 Graph neural network modeling method for collaborative development mechanism of digital economy industrial ecology and artificial intelligence

In order to systematically identify the structural characteristics, transmission paths and action boundaries of the collaborative development of digital economy industrial ecology and artificial intelligence, this paper proposes three testable research hypotheses before entering the model training, and organizes the subsequent network construction and effect analysis.

H1: Under the condition of multi-agent high-frequency interaction, if enterprises, platforms, technologies and regional units are incorporated into the unified collaborative network, the graph structure expression can better reflect the real association state of industrial ecology than the traditional linear index splicing.

H2: In the case of cross-industry and cross-regional heterogeneous connections, multi-relational graph modeling can more accurately identify the diffusion path and coupling strength of artificial intelligence elements in the industrial ecology.

H3: After introducing the ecological awareness and collaborative decision mechanism, the structure representation learned by the graph neural network can improve the stability of collaborative state recognition and optimal decision making.

3.1 Digital economy industrial ecological collaborative network structure design

The industrial ecology of digital economy is not a closed system composed of a single industrial chain, but a composite network formed by platform enterprises, technology service providers, data providers, manufacturing enterprises, financial capital, scientific research institutions and regional carriers in continuous interaction. After artificial intelligence enters this system, it is not attached to a local link, but changes the connection strength and propagation direction between nodes through algorithm embedding, knowledge transfer, data feedback and intelligent decision-making. If the traditional panel variable or single-level input-output relationship is still used to describe, it is often difficult to reflect the cross-dependence and structural nested relationship between multi-agents. Based on this, this paper abstracts the collaborative system as a heterogeneous graph structure composed of multiple types of nodes, multiple semantic edges and hierarchical propagation relations, as shown in Figure 1.

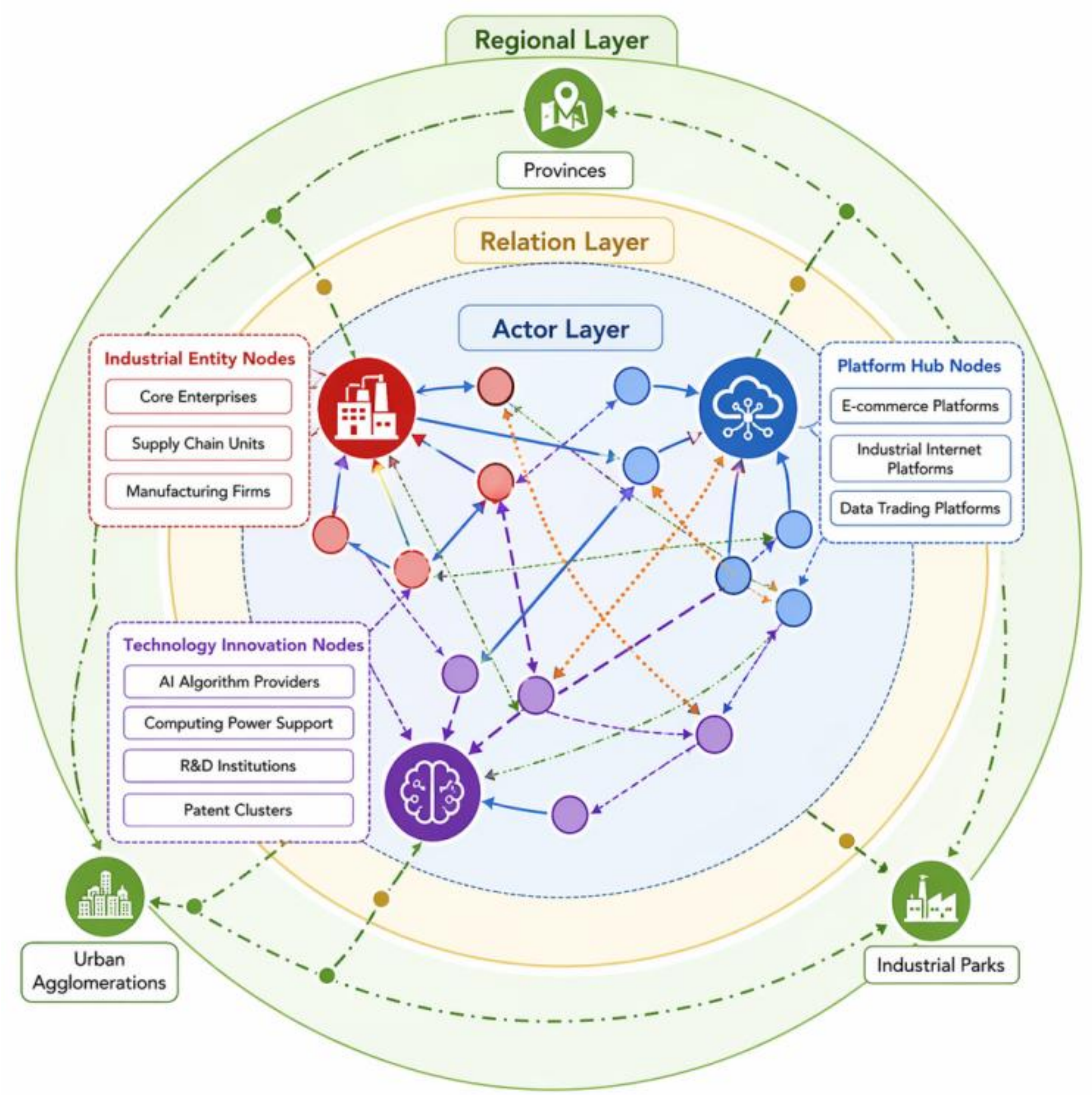

Figure 1: Schematic diagram of the overall structure of the digital economy industrial ecology and artificial intelligence collaborative network

In terms of node design, this paper divides the network agents into four types: industry agent nodes, platform hub nodes, technology innovation nodes and regional carrier nodes. Industrial subject nodes mainly represent core enterprises and collaborative units in different industries, which are used to describe industrial activities, the degree of digital transformation and the ability of value creation. Platform hub nodes are used to represent intermediary structures such as e-commerce platforms, industrial Internet platforms, and data trading platforms, and their role is to enhance resource convergence and cross-domain connectivity. The technology innovation node represents the supply of artificial intelligence algorithms, computing power support, research and development institutions and patent groups, which reflect the injection level of intelligent capabilities. Regional bearing nodes correspond to provinces, urban agglomerations or key parks, and bear the expression of institutional environment, infrastructure and market absorption capacity. The heterogeneous graph is constructed as follows:

$$G=(V,E,R,X) \tag{1}$$

Here, V is the set of nodes, E is the set of edges, R represents the set of relation types, and X is the node attribute matrix. This definition enables multi-source information in industrial ecology to be represented and disseminated under a unified computing framework.

Considering that the links in the industrial ecology of digital economy are not single, this paper further divides the edge relations into four types: industrial collaboration relations, data flow relations, technology supply relations and regional linkage relations. The formation basis of different relationships is not the same: industrial collaboration reflects more input and output, supply and business cooperation; Data flow mainly reflects the frequency of platform interaction, the intensity of interface call and the depth of data sharing. The technology supply relationship emphasizes artificial intelligence model, algorithm service, R&D transformation and knowledge spillover. Regional linkage is related to spatial adjacency, policy coordination and trans-regional flow of innovation resources. In order to improve the interpretability of edge weight construction, this paper uses weighted fusion to define the comprehensive synergy strength between any node i and j as follows.

$$w_{ij}=\lambda_1 s_{ij}^{(c)}+\lambda_2 s_{ij}^{(d)}+\lambda_3 s_{ij}^{(t)}+\lambda_4 s_{ij}^{(r)}, \qquad \sum_{k=1}^{4}\lambda_k=1 \tag{2}$$

Here, $s_{ij}^{(c)}$、$s_{ij}^{(d)}$、$s_{ij}^{(t)}$、$s_{ij}^{(r)}$ represent the collaboration, data, technology and regional relationship strength, respectively, and λk is the corresponding weight. This processing method does not simply superimpose multiple connections, but retains their source differences, which provides the basis for subsequent sub-relation propagation. In the expression of node attributes, this paper no longer uses a single statistical index, but constructs a four-dimensional feature vector of "basic capability-digital percolation-intelligent empower-ecological position". For any node i, its initial representation is denoted as follows.

$$h_i^{(0)}=[x_i^{(b)} \parallel x_i^{(d)} \parallel x_i^{(a)} \parallel x_i^{(e)}] \tag{3}$$

Among them, $x_i^{(b)}$ represents the basic capability characteristics such as operation scale, innovation input, and network foundation. $x_i^{(d)}$ represents the degree of digital platform access, data resource occupancy and digital transformation; $x_i^{(a)}$ represents the depth of AI application, the ability of model deployment and the frequency of algorithm use. $x_i^{(e)}$ represents the centrality, bridging and embedding position of the node in the overall ecology. The design can reflect not only the node's own state, but also its relative functional role in the network.

On this basis, this paper organizes the collaborative network into a three-level nested structure of "subject level-relationship level-region level". The main layer is used to express the direct interaction among enterprises, platforms and technology nodes. The relation layer is responsible for distinguishing different semantic edges and forming multi-channel conduction. The regional layer embeds the local network into the larger-scale spatial and institutional environment to identify the hierarchical differences of collaborative diffusion. The reason for this treatment is that the operation of the industrial ecology of the digital economy does not follow the one-way diffusion logic, but shows a composite process of local aggregation, cross-domain connection and regional redistribution. Figure 2 shows the basic path of multi-relational edge construction and hierarchical conduction in this paper.

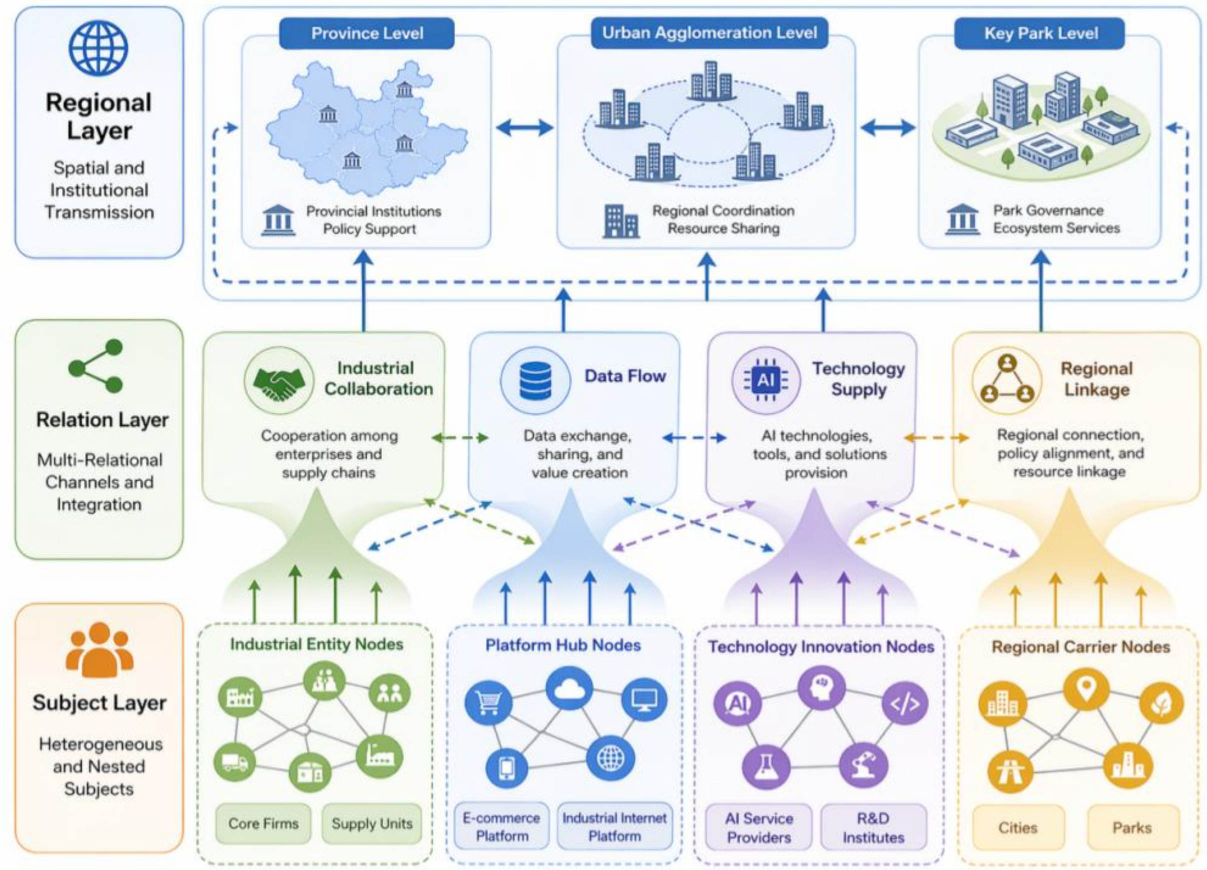

Figure 2: Schematic diagram of multi-relational collaborative edge construction and hierarchical transmission mechanism

In order to characterize the overall coupling degree of the ecosystem after the intervention of artificial intelligence, this paper defines the synergy index at the network layer:

$$C=\frac{1}{|V|}\sum_{i\in V}\sigma\left(W_c h_i^{(0)}+\sum_{j\in N(i)} w_{ij}\, h_j^{(0)}\right) \tag{4}$$

Here, N(i) represents the neighborhood set of node i, W_c is the learnable parameter matrix, and $\sigma(\cdot)$ is the nonlinear mapping function. This index does not directly replace the subsequent model output, but is used to test whether ecological links have sufficient collaborative density and propagation basis in the network construction stage.

In general, the industrial ecological collaborative network of digital economy constructed in this section completes the formal mapping from the real industry connection to the heterogeneous graph structure, and also provides a clear input for the subsequent hierarchical modeling of graph neural network. Its significance does not lie in the graphical representation of industrial relations, but in the organic organization of nodes, edges and hierarchical structures to transform the original scattered industrial activities, the flow of digital factors and the embedding process of artificial intelligence into learnable, interpretable and comparable computing objects. On this basis, the hierarchical propagation and collaborative decision-making mechanism of graph neural network will be further designed.

3.2 Hierarchical modeling method of graph neural network

In the face of heterogeneous networks formed by multi-type nodes such as enterprise, platform, technology and region, if a single-layer graph convolution is directly used for overall propagation, it is easy to have problems such as relational semantic aliasing, local features being overly smoothed, and cross-regional differences being weakened. Based on this, this paper constructs the model as a hierarchical modeling link of "type mapping, relational coding, intra-layer propagation, cross-layer fusion, and collaborative output", so that the information from different sources can be extracted step by step and fused orderly in the unified computing framework.

In the input phase, let the heterogeneous graph constructed in Section 3.1 be G=(V,E,R), and the node initial attributes are represented as $h_i^{(0)}$. Since different node types have obvious differences in economic meaning and feature scale, this paper first introduces the type mapping matrix to uniformly project the original features. For any node i, its initial embedding representation is defined as follows.

$$z_i^{(0)}=P_{\tau(i)}h_i^{(0)}+b_{\tau(i)} \tag{5}$$

Here, τ(i) represents the node type, and $P_{\tau(i)}$ and $b_{\tau(i)}$ represent the projection parameter and bias term of the corresponding type, respectively. Through this mapping, industry subject nodes, platform nodes, technology nodes and regional nodes are transformed into the same potential space, which lays a foundation for subsequent cross-type propagation.

In the relationship coding stage, this paper does not directly merge multiple edge relationships, but establishes propagation channels for different relationships such as industrial cooperation, data flow, technology supply and regional linkage. Let the neighborhood of node i in layer l under relation r be $N_r(i)$, then its relation message aggregation result is expressed as follows.

$$m_{i,r}^{(l)}=\sum_{j\square N_r(i)}\alpha_{ij}^{(r,l)}W_r^{(l)}z_j^{(l)} \tag{6}$$

where, $W_r^{(l)}$ is the transformation matrix of relation r at level l, and $\alpha_{ij}^{(r,l)}$ is the contribution weight of adjacent nodes to the current node. In order to enhance the recognition ability of the model for key connection edges, this paper uses the attention mechanism to calculate the weights:

$$\alpha_{ij}^{(r,l)}=\frac{\exp\left(q_i^{(l)\top}k_j^{(r,l)}\right)}{\sum_{u\square N_r(i)}\exp\left(q_i^{(l)\top}k_u^{(r,l)}\right)} \tag{7}$$

Here, $q_i^{(l)}$ denotes the query vector of node i and $k_j^{(r,l)}$ denotes the key vector of node j under relation r. The design can avoid excessive interference of weak correlation edges on the propagation results, and make the model more sensitive to capture the core role of platform hubs, key technology suppliers and highly connected areas.

In the intra-layer propagation stage, the model jointly updates the aggregated results of each relationship channel and the node's own state to form a node representation with local structure awareness. The update process is written as follows:

$$z_i^{(l+1)}=\psi\left(U^{(l)}z_i^{(l)}+\sum_{r\square R}\beta_r^{(l)}m_{i,r}^{(l)}\right) \tag{8}$$

Here, $U^{(l)}$ is the self-cyclic transformation matrix, $\beta_r^{(l)}$ represents the fusion weights of different relations at the LTH layer, and $\psi(\cdot)$ is the nonlinear activation function. In this way, the node representation not only retains its own characteristics, but also absorbs the structural information of the multi-relational neighborhood, which can more accurately reflect the collaborative embedding state in the industrial ecology of the digital economy.

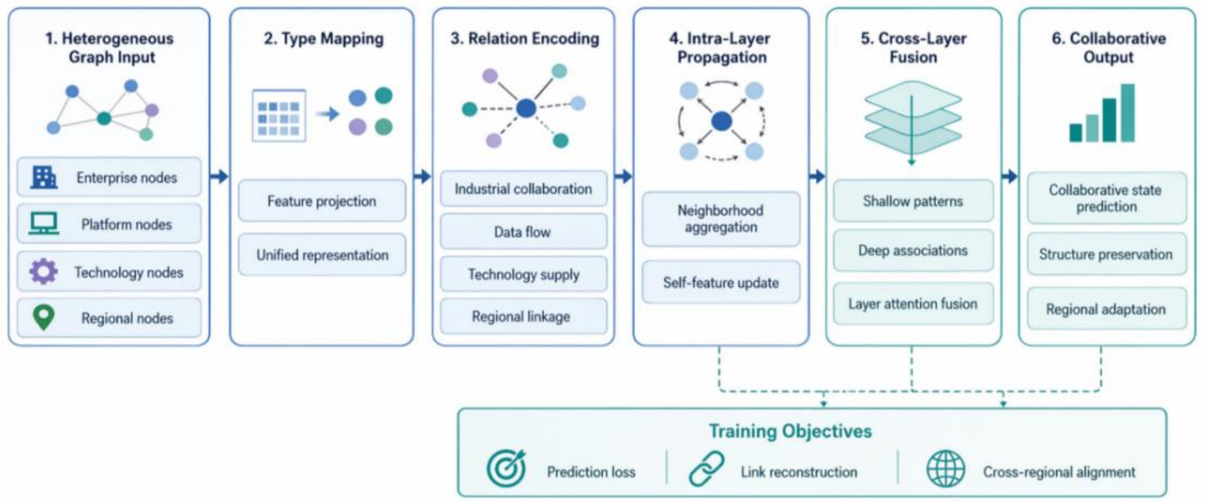

Figure 3: Hierarchical modeling framework of graph neural networks

As shown in Figure 3, the hierarchical model in this paper does not simply superimpose multi-layer graph propagation, but emphasizes the cooperative relationship between "intra-layer extraction" and "cross-layer fusion". Shallow propagation is more suitable for preserving neighbor relations such as direct cooperation, data exchange and technology access, while deep propagation is more conducive to revealing high-order associations such as cross-industry diffusion, cross-regional transmission and ecological location reconstruction. In order to reduce the semantic attenuation caused by deep propagation, we perform attention fusion on the outputs of each layer to form the final node representation, and generate the collaborative state output accordingly. Considering that the data completeness and industry density between different regions are not consistent, the cross-regional distribution correction term is further introduced in the training stage to alleviate the representation shift in the sparse sample areas. The overall objective function is defined as follows.

$$L=L_{task}+\mu L_{link}+\nu D_{mmd}(P_s,P_t) \tag{9}$$

Among them, L_{task} represents the collaborative state prediction loss, L_{link} represents the structural relationship reconstruction loss, $D_{mmd}(P_s,P_t)$ represents the distribution difference constraint between high-density regions and low-density regions, and μ and ν are the trade-off coefficients. The objective function makes the model not only focus on the prediction result itself, but also take into account the network structure maintenance and regional heterogeneous adaptation.

3.3 Collaborative decision-making mechanism of industrial ecological perception and artificial intelligence

The operation state of the industrial ecology of the digital economy does not depend on the growth level of a single node, but is affected by the industrial activity, data mobility, technology penetration, regional carrying capacity and network coordination strength. Without a unified perception mechanism, although the artificial intelligence model can output the structure representation, it is difficult to further support resource matching, path correction and policy optimization. Based on this, on the basis of the graph representation learning results in Section 3.2, this paper constructs a collaborative decision-making link of "indicator perception-state evaluation-policy generation-feedback update", as shown in Figure 4.

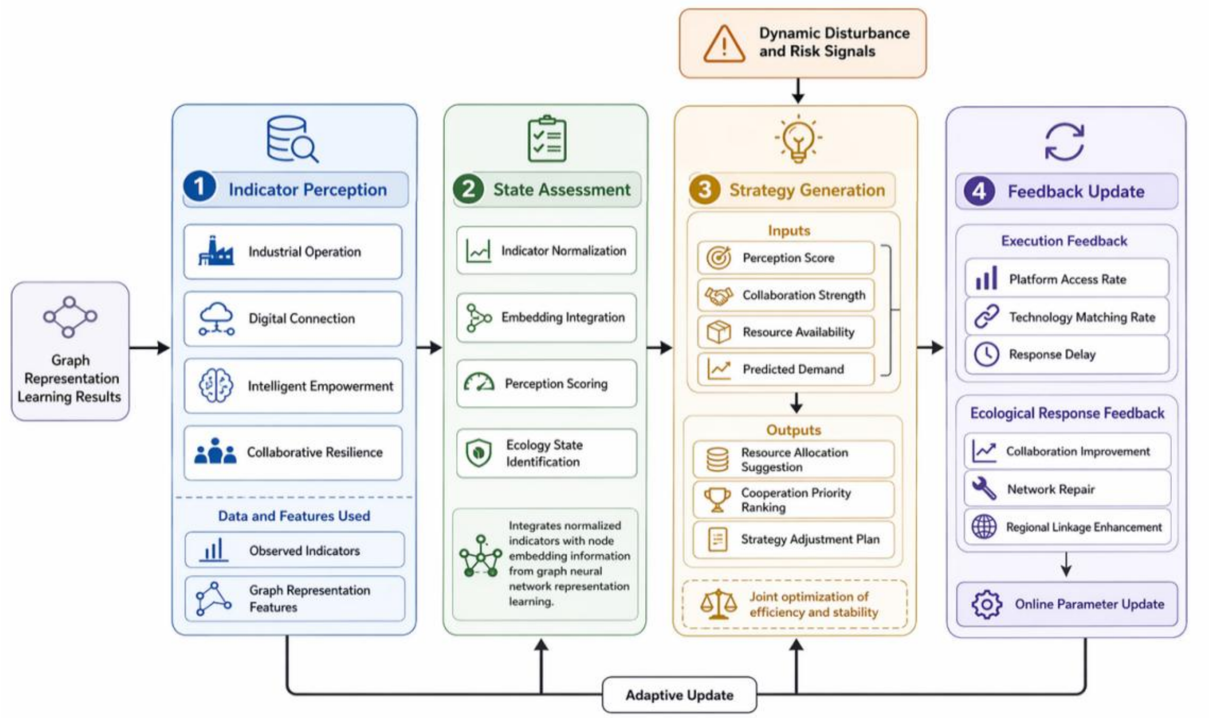

Figure 4: Framework of collaborative decision-making mechanism between industrial eco-awareness and artificial intelligence

In the ecological perception stage, this paper divides the industrial ecological state into four dimensions of industrial operation, digital connection, intelligent empowerment and collaborative resilience, which correspond to the innovation activity of enterprises, the frequency of platform interaction, the application intensity of artificial intelligence and the stability of cross-subject collaboration. Let the observed value of region or industry unit i on index m be $\tilde{x}_{i,m}$, and the result after interval standardization is denoted as follows.

$$\tilde{x}_{i,m}=\frac{x_{i,m}-\min(x_m)}{\max(x_m)-\min(x_m)} \tag{10}$$

On this basis, combined with the node embedding vector z_i obtained in Section 3.2, the comprehensive industrial ecological perception score is constructed as follows.

$$P_i=\sum_{m=1}^{M}\omega_m\tilde{x}_{i,m}+\rho\|z_i\|_2 \tag{11}$$

Here, ω_m is the index weight and ρ is the structural representation regulation coefficient. The score is not only a linear summary of traditional statistical indicators, but also incorporates the network location, connection strength and collaborative embedding state extracted by graph neural network into the evaluation, so that the perception results are closer to the operation characteristics of real industrial ecology.

In the collaborative decision-making stage, the inputs of the artificial intelligence decision engine are set as ecological perception score, collaborative relationship strength, node resource availability and predicted demand vector, and the output results are cross-agent resource allocation suggestions, cooperation priority ordering and strategy adjustment scheme. Considering that the industrial ecology of digital economy not only pursues allocative efficiency, but also emphasizes cross-regional and cross-industry collaborative equilibrium, this paper defines the decision-making objective as a joint optimization problem of efficiency gain and collaborative stability:

$$\max U_t = \sum_{i=1}^{N} \pi_{i,t} \frac{A_{i,t}}{D_{i,t}+\varepsilon} + \kappa \sum_{i=1}^{N} S_{i,t} - \lambda_t \mathrm{Var}(P_i) \tag{12}$$

where U_t is the comprehensive collaborative utility at time t, $\pi_{i,t}$ represents the node priority weight, $A_{i,t}$ and $D_{i,t}$ represent the actual allocation quantity and predicted demand respectively, $S_{i,t}$ represents the collaborative benefit, $\mathrm{Var}(P_i)$ is used to measure the degree of ecological state dispersion between different units, λ_t is the equilibrium constraint strength. The implication of this objective function is that when some regions or industries are excessively concentrated due to the advantages of data, technology or platform, the model will moderately increase the weight of the equilibrium term to avoid the continuous concentration of collaborative resources to a few high-density nodes. In order to enhance the situational adaptability of the decision-making mechanism, this paper further introduces a dynamic adjustment function to update the equilibrium parameters in real time:

$$\lambda_t = \sigma(\lambda_0 + \xi \Delta_t + \zeta R_t) \tag{13}$$

where λ_0 is the initial weight, Δ_t represents the intensity of stage fluctuation, R_t represents the level of external risk disturbance, ξ and ζ are the adjustment coefficients, and $\sigma(\cdot)$ is the compression function. In this way, the system will emphasize more on efficiency when the industrial linkage is stable and the matching degree of resource supply and demand is high. When the external shock is enhanced or the imbalance of synergy relationship is aggravated, the model will automatically improve the equilibrium constraint to suppress the extrusion effect caused by the excessive expansion of local nodes on the overall ecology.

In the feedback update stage, this paper divides the evaluation of decision-making effect into two levels: behavior execution feedback and ecological response feedback. The former focuses on the implementation indicators such as platform access rate, technology matching rate and cooperation response delay after the policy is issued, and the latter focuses on the outcome indicators such as the improvement of collaboration intensity, network fracture repair and improvement of regional linkage. In order to improve the efficiency of parameter search, the model uses an online optimization method based on expected utility to update the policy parameter θ iteratively:

$$\theta^* = \arg\max_{\theta \in \Theta} E[U(\theta) \mid D_{1:t}] \tag{14}$$

Here, Θ denotes the parameter space and $D_{1:t}$ denotes the set of feedback data up to time

t. By continuously absorbing a new round of execution information, the decision system can form an adaptive fine-tuning ability under different industrial stages and regional conditions.

Overall, the collaborative decision-making mechanism of industrial ecological perception and artificial intelligence constructed in this section further transforms the structural representation obtained by the graph neural network into an interpretable and executable policy output process. On the one hand, it strengthens the dynamic identification of the digital economy industry ecological operation state; On the other hand, it also provides a quantifiable decision-making basis for subsequent effect analysis, so that the model does not stay at the relationship recognition level, but can enter the practical application level of collaborative optimization and feedback correction.

4 Effect analysis of the collaborative development mechanism of digital economy industrial ecology and artificial intelligence driven by graph neural network

4.1 Model performance evaluation

In order to test the effectiveness of the graph neural network model constructed in this paper in the collaborative identification of digital economy industry ecology, this paper constructs experimental samples based on the data of provincial digital economy development, artificial intelligence industry investment, platform connection strength, technology diffusion relationship and cross-regional collaboration network from 2018 to 2024, and divides the training set, validation set and test set according to 7：1：2. The evaluation indicators are Accuracy, Macro-F1 and AUC to simultaneously investigate the performance of the model on the overall discrimination ability, class balance recognition ability and collaborative state discrimination ability. The comparison models include traditional Support Vector Machine (SVM), Random Forest, Graph Convolutional Network (GCN) and Graph Attention Network (GAT). Among them, SVM and random forest are mainly used to observe the baseline level of non-graph structure models, while GCN and GAT are used to compare the differences of different graph learning methods in industrial ecological relationship modeling.

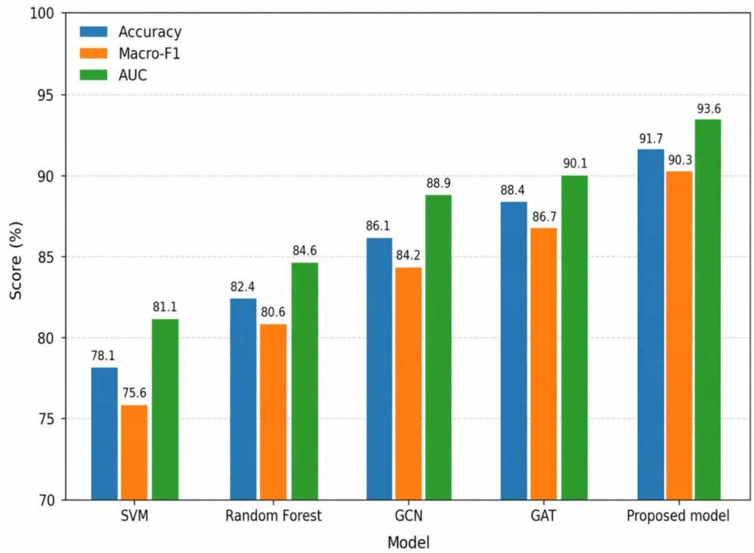

Figure 5: Comparison of model performance

The experimental results show that the proposed model has obvious advantages in the three core indicators. As shown in Figure 5, the Accuracy of SVM, random forest, GCN, GAT and the proposed model is 78.1%, 82.4%, 86.1%, 88.4% and 91.7%, respectively. Macro-F1 was 75.6%, 80.6%, 84.2%, 86.7% and 90.3%, respectively; The AUC was 81.1%, 84.6%, 88.9%, 90.1% and 93.6%, respectively. Compared with traditional machine learning methods, the proposed model has a more prominent improvement in the expression of structural relations. Taking AUC as an example, it is 12.5 percentage points higher than that of SVM and 9.0 percentage points higher than that of random forest, indicating that after the industrial subject, platform node, technology supply node and regional unit are integrated into the unified graph structure, the model can more accurately identify the collaborative boundary and linkage strength in the industrial ecology of digital economy.

Compared with two typical graph models, the proposed model also shows better comprehensive performance. Compared with GCN, the Accuracy is increased by 5.6 percentage points, Macro-F1 is increased by 6.1 percentage points, and AUC is increased by 4.7 percentage points. Compared with GAT, the three indicators also increased by 3.3, 3.6 and 3.5 percentage points, respectively. This indicates that only relying on a single neighborhood aggregation or general attention allocation is still difficult to fully describe the complex structure of multi-type nodes, multi-relationship channels and cross-level propagation in the industrial ecology of digital economy. By introducing hierarchical representation learning and collaborative state constraints, the model in this paper enhances the extraction ability of high-order relationships and heterogeneous conduction paths while maintaining local connection information. Therefore, the model is more stable in the discrimination of collaborative states, and is more in line with the analysis requirements of this study on the coupling mechanism between industrial ecology and artificial intelligence.

4.2 Analysis on collaborative optimization effect of digital economy industrial ecology and artificial intelligence

In order to test the actual role of the graph neural network model constructed in this paper in the collaborative optimization level, four types of representative regional units are selected to carry out comparative analysis before and after optimization, which are respectively denoted as A digital manufacturing agglomeration area, B platform service hub area, C technology transformation linkage area and D industrial transformation undertake area. The comparison objects are divided into two groups: one is the conventional configuration scheme without introducing the collaborative decision mechanism of the graph neural network, and the other is the proposed graph neural network driven collaborative optimization scheme. The evaluation indicators include collaborative efficiency index, cross-subject linkage degree and artificial intelligence matching rate, which reflect the internal resource organization efficiency of industrial ecology, the connection level between enterprise-platex-technology nodes, and the response accuracy of artificial intelligence to industrial demand. The results are shown in Figure 6.

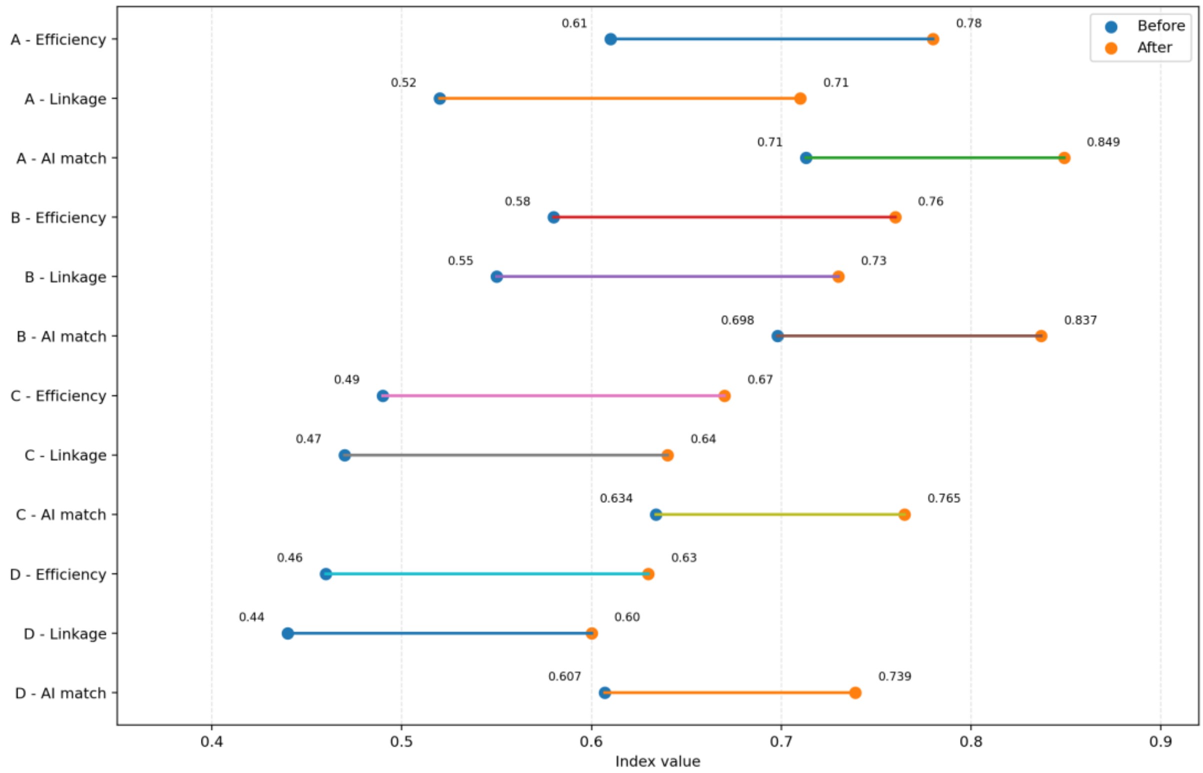

Figure 6: Comparison of typical regions before and after collaborative optimization

Figure 6 shows that the four types of regions show a relatively obvious trend of improvement after the proposed method is adopted. In terms of collaborative efficiency index, region A is increased from 0.61 to 0.78, region B is increased from 0.58 to 0.76, region C is increased from 0.49 to 0.67, and region D is increased from 0.46 to 0.63, indicating that graph neural network has a strong role in identifying key relationship edges, optimizing node configuration paths, and inhibiting inefficient connections. The degree of cross-subject linkage also improved significantly, and the four categories of areas A, B, C and D increased from 0.52, 0.55, 0.47 and 0.44 to 0.71, 0.73, 0.64 and 0.60 respectively, indicating that the collaborative transmission chain was further opened between platforms, enterprises and technology supply subjects. The flow of information, technology and cooperation within the industrial ecology is smoother.

The improvement of artificial intelligence matching rate is also relatively stable. Region A increased from 0.713 to 0.849, region B increased from 0.698 to 0.837, region C increased from 0.634 to 0.765, and region D increased from 0.607 to 0.739. The results show that after introducing the ecological awareness and collaborative decision-making mechanism, the model can more accurately identify the differences in industrial demand in different regions, and more effectively couple algorithm resources, data resources and application scenarios. In contrast, the two types of areas A and B have a larger improvement range, which is related to their better platform foundation, higher node connection density, and more mature artificial intelligence application conditions. Although the absolute level of C and D regions is slightly lower, the increase rate is still considerable after optimization, indicating that the proposed method is also suitable for transformation-type and continuation-type regions.

4.3 Analysis of differences between industry level and regional level

In order to further test the adaptation ability of graph neural network model in different industrial structures and regional levels, this paper conducts cross analysis from two dimensions of industry level and regional level. The industry level is divided into digital manufacturing, platform service and intelligent application industries, and the regional level is divided into first-tier cities, second-tier cities and county areas. Considering that different sample units have obvious differences in digital infrastructure, platform connection strength, artificial intelligence application density, and industrial collaboration depth, it is often difficult to reveal the real performance of the model in heterogeneous scenarios if only the average comparison of the overall sample is performed. Based on this, this paper sets the representative region sample A-I to compare the differences in the collaborative adaptation index of different regions, and combines the artificial intelligence matching rate and the average response time to further analyze the operation characteristics of the model in various scenarios.

Figure 7 shows the co-adaptation index of the nine sample units. This index comprehensively reflects the identification effect of industrial ecological structure, the propagation efficiency of collaborative relationship and the configuration coordination level after artificial intelligence embedding. The higher the value, the better the adaptation effect of the model in the corresponding scene. From the results, the three regional indexes of A, B and C in the first-tier cities are 0.892, 0.876 and 0.821, respectively, which are at a high level, indicating that under the conditions of perfect digital base, dense node connection and stable platform data flow, graph neural network can fully extract cross-subject association relationships and form a strong collaborative recognition ability. The three regional indexes of D, E, and F in second-tier cities are 0.844, 0.826, and 0.768, respectively, which are slightly lower than those in first-tier cities, but still maintain a good adaptation level as a whole, indicating that the model also has strong generalization ability in medium-scale industrial ecology. The three regional indexes of G, H and I in the county area are 0.781, 0.752 and 0.694, respectively, and the downward trend is obvious, which indicates that the learning effect of the model for high-order relationships will be restricted under the conditions of sparse node distribution, low data update frequency and weak collaborative relationships.

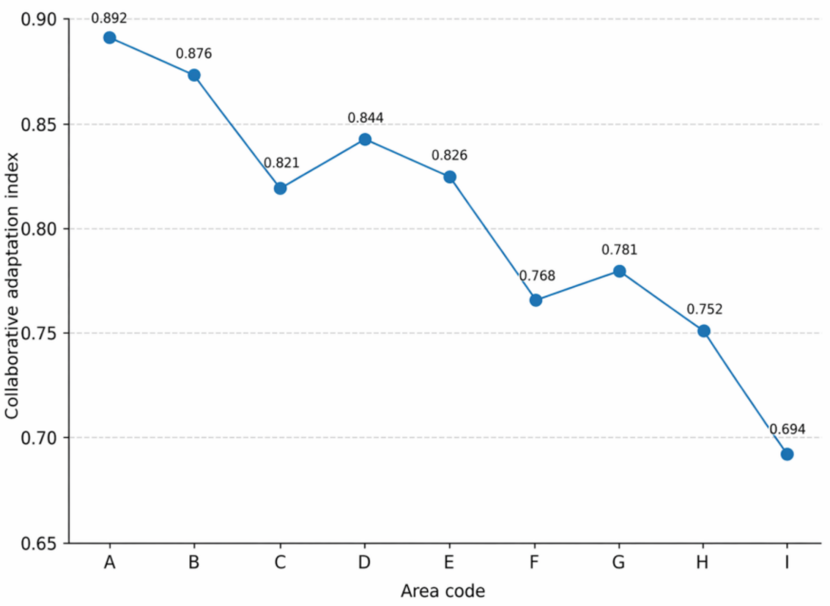

Figure 7: Comparison of collaborative adaptation index between industry level and region level

By industry type, the overall performance of digital manufacturing is the most prominent. The three regions A, D, and G are all higher than the other two industries at the same level in their respective levels, which is closely related to the clear connection relationship of equipment, the stable path of data collection, and the clear chain of enterprise collaboration in the manufacturing scene. The platform service industry is in the middle level. Although B, E and H regions have strong data flow advantages, they have higher requirements for the dynamic adaptation of the model due to the large volatility of user demand and rapid change of behavior patterns. The adaptation index of intelligent application industry is relatively low, and the decline of C, F, and I regions is more obvious, indicating that although the degree of artificial intelligence embedding is high in this kind of scene, its application boundary changes more frequently, the node relationship updates faster, and the model faces greater structural disturbance when migrating across stages.

To illustrate this difference more specifically, Table 2 further lists the AI matching rate and average response time for samples from each region. It can be seen that the artificial intelligence matching rate of digital manufacturing sample A in first-tier cities reaches 0.861, and the average response time is 1.42 s, which is the best performance in all samples. The matching rates of the platform service industry sample B and the intelligent application industry sample C in first-tier cities were 0.847 and 0.803, respectively, and the average response time was 1.56 s and 1.73 s, respectively, which still maintained a high level. The overall sample of second-tier cities decreased slightly, and the matching rates of D, E and F were 0.823, 0.811 and 0.756, respectively, and the average response time was 1.69 s, 1.84 s and 2.08 s, respectively. The matching rates of G, H and I regions were 0.764, 0.739 and 0.681, respectively, and the average response time extended to 2.14 s, 2.37 s and 2.68 s. The results show that the lower the regional level is, the more susceptible the model inference efficiency and matching accuracy are to the impact of infrastructure, data synchronization frequency and collaborative network density.

Table 2: Artificial intelligence matching rate and average response time of samples at different industry levels and regional levels

Region Code	Regional Level	Dominant Industry Type	AI Matching Rate	Average Response Time / s
A	First-tier city	Digital manufacturing	0.861	1.42
B	First-tier city	Platform service industry	0.847	1.56
C	First-tier city	Intelligent application industry	0.803	1.73
D	Second-tier city	Digital manufacturing	0.823	1.69
E	Second-tier city	Platform service industry	0.811	1.84
F	Second-tier city	Intelligent application industry	0.756	2.08
G	County-level area	Digital manufacturing	0.764	2.14
H	County-level area	Platform service industry	0.739	2.37
I	County-level area	Intelligent application industry	0.681	2.68

On the whole, graph neural network models show good applicability in different industries and different regions, but their advantages are more significant in scenarios with high connectivity and high data density. For first-tier cities and digital manufacturing, the model can more effectively mine stable collaborative links. For the county area and intelligent application industry, it is still necessary to further improve the adaptation ability by enhancing the connection of heterogeneous nodes, improving the efficiency of data synchronization, and optimizing the small sample migration mechanism. This also shows that the collaborative development of digital economy industrial ecology and artificial intelligence is not a homogeneous process, and its implementation effect will show obvious differences with the difference of regional foundation, industry structure and network density.

4.4 Analysis of abnormal situations and boundary conditions

In the collaborative operation process of digital economy industrial ecology and artificial intelligence, the model is not always in an ideal environment with complete data, stable connection and continuous structure. The short-time loss of regional platform, the exit of key enterprise nodes, the delay of cross-regional data synchronization and the abnormal loss of local relationship edges will change the information propagation path in the graph structure, and further affect the stability of collaborative recognition results and decision output. If the effectiveness of the model is judged only by the performance results under regular samples, it is still not enough to explain its application boundary in complex industrial ecology. Based on this, this paper further sets up two test scenarios of abnormal disturbance and deployment boundary to test the recognition accuracy, strategy stability and response time of the model under extreme conditions.

The abnormal test part mainly includes three types of scenarios. The first is the failure of key nodes, that is, some platform nodes or industrial hub nodes temporarily withdraw from the collaboration cycle. The second is data synchronization delay, that is, there is an obvious lag in inter-region relationship update and parameter transmission. The third is the relationship edge missing disturbance, that is, part of the cooperation edges, data flow edges or technology supply edges in the graph structure cannot be observed in time. Table 3 shows the test results of the proposed model under different abnormal intensities. It can be seen that when the failure ratio of key nodes increases from 10% to 20%, the collaborative recognition accuracy decreases from 89.8% to 86.9%, the average response time increases from 1.78 s to 2.06 s, and the policy drift index increases from 0.08 to 0.13, indicating that the exit of core nodes will weaken the information integrity of local subgraphs. However, the model can still maintain a high level of basic recognition ability. When the delay time increases from 30 minutes to 60 minutes, the accuracy decreases from 88.7% to 85.6%, and the strategy drift index increases to 0.16, which indicates that the lag of edge weight update will cause the phase deviation of cross-regional collaboration. Even if the proportion of missing relationship edges reaches 30%, the accuracy of the model still remains at 84.8%, which indicates that the hierarchical graph representation mechanism has a certain fault-tolerant ability to local weak connection breaks.

Table 3: Stress test results of the proposed model under abnormal circumstances

Anomaly Type	Disturbance Intensity	Collaborative Recognition Accuracy / %	Average Response Time / s	Strategy Drift Index
Critical node failure	10%	89.8	1.78	0.08
Critical node failure	20%	86.9	2.06	0.13
Data synchronization delay	30 min	88.7	1.92	0.11
Data synchronization delay	60 min	85.6	2.24	0.16
Relationship edge missing	10%	89.1	1.85	0.09
Relationship edge missing	20%	86.3	2.01	0.12
Relationship edge missing	30%	84.8	2.18	0.15

From the perspective of error sources, the performance fluctuation under abnormal conditions mainly comes from three aspects. Firstly, the failure of key nodes will break the bridging effect of original high centrality nodes, shorten the propagation chain of local relations, and reduce the availability of high-order structural information. Secondly, the data synchronization delay leads to the out-of-sync update of graph representation between regions, so that the model still relies on the old relationship state to make judgments in a short window, which is easy to cause slow output of the policy. Third, the lack of relationship edges will weaken the expression ability of potential collaborative paths such as technology diffusion and platform connectivity, especially in low-density regions. In general, although the model in this paper is subject to disturbance impact, it still maintains good robustness when the abnormal proportion has not exceeded a high threshold.

In addition to abnormal perturbations, model performance is also constrained by deployment conditions. Considering the differences in digital infrastructure, platform connection density and intelligent computing resources in different regions, we further investigate the impact of changes in edge node deployment density on model performance. Table 4 shows that as the coverage rate of edge nodes increases from 10% to 50%, the collaborative recognition accuracy increases from 83.7% to 91.2%, the average response time decreases from 2.31 s to 1.53 s, and the artificial intelligence matching rate increases from 0.712 to 0.861. The results show that the increase of edge node density is helpful to improve the local perception ability and the frequency of relationship update, so as to strengthen the real-time description ability of the model for dynamic industrial ecology. However, when the coverage rate exceeds 40%, the improvement range of each indicator Narrows significantly, indicating that the system performance has begun to enter the marginal stable interval, and the benefits brought by continuing to increase the deployment scale have been relatively limited.

Table 4: Impact of edge node deployment density on model performance

Edge Node Coverage / %	Collaborative Recognition Accuracy / %	Average Response Time / s	AI Matching Rate
10	83.7	2.31	0.712
20	86.5	1.97	0.768
30	88.9	1.74	0.812
40	90.8	1.58	0.849
50	91.2	1.53	0.861

In summary, the proposed model can still maintain basic stability under abnormal conditions such as key node failure, data delay and missing relationship edges, indicating that the collaboration mechanism driven by graph neural network has good anti-disturbance ability. However, under the condition of high intensity synchronization delay and low density deployment, the performance of the model will decrease significantly, indicating that its effective operation still depends on a certain data update frequency and network coverage foundation.

5 Discussion

Compared with SVM, random forest, GCN, GAT and other contrast models, the graph neural network collaborative modeling method constructed in this paper shows more stable comprehensive advantages in the identification of industrial ecological relations in digital economy and the collaborative decision-making of artificial intelligence. The Accuracy of the model on the test set reached 91.7%, Macro-F1 reached 90.3%, and AUC reached 93.6%, which were 5.6, 6.1, and 4.7 percentage points higher than those of GCN, respectively, indicating that after incorporating industrial subjects, platform nodes, technology supply nodes and regional units into the unified graph structure, It can more fully identify the high-order association and cross-layer conduction path between multi-agents. Section 4.2 further shows that the collaborative optimization mechanism does not stop at the structure recognition level, and the collaborative efficiency index of the four typical regions A, B, C and D is significantly improved, where the A region is increased from 0.61 to 0.78, and the B region is increased from 0.58 to 0.76, and the artificial intelligence matching rate is also increased to 0.849 and 0.837, respectively. It reflects that graph structure learning can substantially improve the accuracy of resource allocation and the strength of collaborative linkage.

From the hierarchical results, the advantages of the model are more prominent in the regions with high connection density and high data completeness. The collaborative adaptation index of samples A, B and C in first-tier cities reached 0.892, 0.876 and 0.821, respectively, which were higher than 0.781, 0.752 and 0.694 in county areas, indicating that digital infrastructure, platform connectivity ability and edge node coverage level were still important conditions affecting the play of collaborative mechanism. The abnormal test results also show that the collaborative recognition accuracy of the model remains between 84.8%-86.9% under the disturbance of 20% critical node failure, 60 min data synchronization delay and 30% missing relationship edges, which reflects a good anti-interference ability. However, when the regional connectivity is too sparse, the relationship update continues to lag, or the key nodes fail for a long time, the model performance will still decline significantly. It can be seen that graph neural network provides a strong structural analysis tool for the collaborative development of digital economy industry ecology and artificial intelligence, but its application effect is still restricted by regional digital base, network density and data synchronization ability.

6 Conclusions

Focusing on the complex correlation characteristics of the collaborative development of digital economy industry ecology and artificial intelligence, this paper constructs a collaborative modeling framework driven by graph neural network. The system completes the design of collaborative network structure, hierarchical representation learning, ecological perception and intelligent decision-making mechanism construction, and multi-dimensional test of the model effect. The research results show that the proposed model performs well in terms of collaborative recognition Accuracy, optimal configuration ability and abnormal disturbance adaptability. The test set accuracy reaches 91.7%, Macro-F1 reaches 90.3%, and AUC reaches 93.6%. The collaborative efficiency index, cross-agent interaction degree and artificial intelligence matching rate of typical regions are also significantly improved, indicating that the graph neural network can effectively describe the multi-agent relationship, cross-layer propagation path and co-evolution law in the digital economy industrial ecology. At the same time, the model still maintains strong stability under the conditions of critical node failure, data synchronization delay and relationship edge missing, which indicates that it has certain practical application potential. However, in county areas, low-density connection areas, and intelligent application industry scenarios, the model performance is still restricted by data completeness, network coverage level, and relationship update frequency. Subsequent research can further introduce small sample transfer, adaptive anomaly detection and dynamic graph update mechanisms to enhance the generalization ability and decision robustness of the model in weak connection and strong fluctuation scenarios.

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References

[1] Tijani B, Oyinlola M, Okoya S A. Digital innovation ecosystem for the circular plastic economy[M]//Digital Innovations for a Circular Plastic Economy in Africa. Routledge, 2023: 76-88.

[2] Oyinlola M, Kolade O, Schröder P, et al. The environment for a digitally enabled circular plastics economy in Africa: lessons from cross-sectional stakeholder engagements[J]. Journal of Strategy and Management, 2024.

[3] Wasi A T, Islam M D, Akib A R, et al. Graph neural networks in supply chain analytics and optimization: Concepts, perspectives, dataset and benchmarks[J]. arXiv preprint arXiv:2411.08550, 2024.

[4] Nagy L, Abonyi J, Ruppert T. Knowledge graph-based framework to support human-centered collaborative manufacturing in Industry 5.0[J]. Applied Sciences, 2024, 14(8): 3398.

[5] Hruskova M. Ecosystem pipelines: Collective action in entrepreneurial ecosystems[J]. International Small Business Journal, 2024, 42(1): 39-66.

[6] Roundy P T. Artificial intelligence and entrepreneurial ecosystems: understanding the implications of algorithmic decision-making for startup communities[J]. Journal of Ethics in Entrepreneurship and Technology, 2022, 2(1): 23-38.

[7] Knox S, Arshed N. Network governance and coordination of a regional entrepreneurial ecosystem[J]. Regional Studies, 2022, 56(7): 1161-1175.

[8] Oyinlola M, Schröder P, Whitehead T, et al. Digital innovations for transitioning to circular plastic value chains in Africa[J]. Africa Journal of Management, 2022, 8(1): 83-108.

[9] Roundy P T, Evans W R. Entrepreneurial ecosystems as multiteam systems: Navigating independence and interdependence in the leadership of startup communities[J]. Journal of Business Venturing Insights, 2024, 21: e00445.

[10] Fuentes N, Schmutzler J, Vargas A M. Unpacking the multilayered nature of entrepreneurial ecosystems: A conceptual complex adaptive system model[J]. International Journal of Innovation Studies, 2024, 8(4): 335-350.

[11] Baldwin C Y, Bogers M L A M, Kapoor R, et al. Focusing the ecosystem lens on innovation studies[J]. Research Policy, 2024, 53(3): 104949.

[12] Roundy P T, Asllani A. Understanding AI innovation contexts: a review and content analysis of artificial intelligence and entrepreneurial ecosystems research[J]. Industrial Management & Data Systems, 2024, 124(7): 2333-2363.

[13] Nam J, Jung Y, Kim J. Understandings of the AI business ecosystem in South Korea: AI startups' perspective[J]. Telecommunications Policy, 2024, 48(6): 102763.

[14] Krause F, Paulheim H, Kiesling E, et al. Managing human-AI collaborations within Industry 5.0 scenarios via knowledge graphs: key challenges and lessons learned[J]. Frontiers in Artificial Intelligence, 2024, 7: 1247712.

[15] Kosasih E E, Brintrup A. A machine learning approach for predicting hidden links in supply chain with graph neural networks[J]. International Journal of Production Research, 2022, 60(17): 5380-5393.

[16] Kosasih E E, Margaroli F, Gelli S, et al. Towards knowledge graph reasoning for supply chain risk management using graph neural networks[J]. International Journal of Production Research, 2024, 62(15): 5596-5612.

[17] Longa A, Lachi V, Santin G, et al. Graph neural networks for temporal graphs: State of the art, open challenges, and opportunities[J]. arXiv preprint arXiv:2302.01018, 2023.

[18] Basole R C, Park H, Seuss C D. Complex business ecosystem intelligence using AI-powered visual analytics[J]. Decision Support Systems, 2024, 178: 114133.

[19] Toorajipour R, Oghazi P, Palmié M. Data ecosystem business models: Value propositions and value capture with Artificial Intelligence of Things[J]. International Journal of Information Management, 2024, 78: 102804.

[20] Sjödin D, Liljeborg A, Mutter S. Conceptualizing ecosystem management capabilities: managing the ecosystem-organization interface[J]. Technological forecasting and social change, 2024, 200: 123187.