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Research on digital economy Promoting the Construction of innovation ecosystem in Chengdu-Chongqing Economic Circle in the era of artificial intelligence

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SUMMARY: *In order to explore how the digital economy reshaped the innovation ecosystem of Shuangcheng Economic Circle in Chengdu-Chongqing region, this paper proposed an artificial intelligent-driven construction framework that integrated multi-source innovation factor clustering, spatio-temporal graph neural network and dynamic feedback update. Firstly, the framework divided enterprises, research institutions, platforms, funds and policy resources into collaborative units from heterogeneous regional data. Then, cross-regional knowledge flows, industrial linkages, and innovation interactions are modeled through spatio-temporal graph representations to infer ecosystem association strength. The feedback update module is further introduced to correct the structural bias and stabilize the evolution estimation. Experiments were carried out on 42,318 records collected from 38 districts and counties. The results show that the proposed model achieves 93.4% construction accuracy and 91.7% collaborative recall rate, and the overall performance is stable better than that of comparison methods and similar models. The verification results provide a computable analysis basis for the regional innovation governance, resource allocation and smart policy adjustment of the twin-city innovation network under the background of digital transformation.*

KEYWORDS: *Artificial intelligence; Digital economy; Innovation ecology; Spatio-temporal Graph Neural Networks*

1 Introduction

In the era of artificial intelligence, digital economy is reorganizing regional innovation resource allocation, knowledge diffusion path and industrial coordination structure. The Chengdu-Chongqing twin-city economic circle brings together platform data, scientific research institutions, manufacturing enterprises, capital networks and public services, and the innovation activities have shown obvious characteristics of data, network and space-time coupling. Enholm I M et al. systematically summarized the relationship between artificial intelligence and business value, indicating that intelligent analysis technology can reshape the way of generating organizational value [1]. Mann G et al. studied the ecological orchestration mechanism in digital transformation and pointed out that cross-agent collaboration needs stable data connection and structural support [2]. Wirtz B W et al. conducted empirical research on open government data and proposed that high-quality data opening can help enhance the efficiency of innovation linkage [3]. Beverungen D et al. proposed that data

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space has become an important infrastructure for digital transformation, which can support cross-border sharing and collaborative computing [4]. Reggi L et al. studied the network relationship in the open data ecosystem and revealed that there is a continuous data collaboration structure among the government, users and organizations [5]. Based on this background, this paper proposes an intelligent analysis framework for the construction of innovation ecology in Chengdu-Chongqing twin cities.

This paper is devoted to the structural identification and dynamic characterization of the regional innovation ecosystem driven by digital economy with the help of computer modeling methods. Nasiri M et al. studied the shaping effect of digital capability on digital innovation and showed that there is a computable correlation between capability structure and innovation results [6]. Pappas I O et al. proposed that responsible digital transformation needs to incorporate technical capabilities and social collaboration into a unified analysis framework [7]. Zahra SA et al. studied the realization path of digital technology to promote the evolution of entrepreneurial ecology, emphasizing the linkage effect of platform connection, resource reorganization and knowledge diffusion [8]. Bejjani M et al. systematically combed the research on digital entrepreneurial ecology and pointed out that digital infrastructure, data interaction and network embedding jointly affect the ecological operation state [9]. Holstein J et al proposed the design method of analysis-oriented data cleaning and understanding system, which provided technical support for high-quality modeling in complex data environment [10]. Based on this, this paper integrates enterprise innovation activities, patent collaboration relationships, scientific research project records and platform interaction data to construct spatio-temporal heterogeneous data sets.

The contribution of this paper is to propose an intelligent modeling approach for the construction of innovation ecology in Chengdu-Chongqing twin cities. Based on multi-source heterogeneous innovation factor data clustering and collaborative unit division, the innovation ecological correlation modeling is completed by spatio-temporal graph neural network, and then the stability of the results is improved by dynamic correction and feedback update mechanism. Compared with single statistical analysis, the framework can simultaneously express the heterogeneity of innovation subjects, the dynamics of regional connections and the evolution of ecological structures, which makes digital economy, technology flow and collaborative response enter a unified computing space, and provides a quantifiable basis for the evaluation of innovation ecology construction effect and the verification of collaborative effects.

The innovation of this paper is reflected in three levels: unified representation, association learning and feedback correction. Multi-type innovation subjects and supporting elements are mapped to computable nodes, cross-regional connections are represented as dynamic graph structures, and the model output can be continuously updated according to real observations, so as to enhance the accuracy and adaptability of ecological construction analysis.

Finally, the structure of the paper is given: Section 2 reviews the related research, Section 3 introduces the model design, Section 4 analyzes the results, Section 5 discusses, and Section 6 gives the conclusion.

2 Related work

The digital economy driven by artificial intelligence is changing the organization way of regional innovation ecology, and data flow, knowledge flow, capital flow and platform connection are gradually incorporated into a unified computing framework. Baltakys K et al. studied the trading behavior prediction of socially connected investors, proposed a behavior modeling method based on graph neural network, and proved that the relational network representation could improve the recognition accuracy of complex agent interactions [11]. This study shows that in the multi-agent connection environment, it is difficult to describe the real collaboration state by only relying on static indicators, and graph structure learning is more suitable to express the interaction strength between regional innovation agents. Kang M et al. studied the identification of digital resource clusters in software ecosystems, and proposed an analysis framework for digital resource clustering to find resource combinations and structural boundaries within ecosystems [12]. This idea provides a direct reference for the division of collaborative units of innovation elements, indicating that heterogeneous resources can be formed into interpretable functional partitions by clustering calculation. Guo C et al. studied the construction of digital economy development index and proposed an improved hierarchical data envelopment analysis method to realize the quantitative evaluation of digital economy development level [13]. By compressing the multidimensional indicators into comparable calculation results, this study provides a stable quantitative basis for input representation in the construction of regional innovation ecology. Wang Q studied the interpretable decision model for sustainable digital economy, and proposed an interpretable calculation mechanism under the condition of uncertain weights, which made the decision output have stronger transparency and adaptability [14]. This result shows that regional innovation ecological modeling cannot only pursue predictive performance, but also need to take into account both result interpretation and governance usability.

Hansen HFet al. studied the diffusion process of artificial intelligence and proposed the AI capability maturity model to describe the evolution level of organizations from technology access to capability deepening [15]. This model provides a transferable analysis perspective for identifying the differences in intelligent application level of innovation subjects in Chengdu-Chongqing twin cities. Breiter K et al. studied the dynamic capability climbing process in dual transformation and proposed the capability maturity modeling scheme to explain the periodic transition of organizations in digital and sustainable transformation [16]. This study shows that the ecosystem is not a static structure, but a dynamic network that is constantly reconstructed with the accumulation of capacity. Basole R C et al. studied complex business ecological intelligence and proposed an AI-driven visual analytics method to transform multi-dimensional relationship networks into interactive structural insights [17]. This method enhances the observability of complex ecology and provides technical support for the identification of spatio-temporal evolution of regional innovation ecology. In order to more clearly compare the differences in the expression of objects, methods and results of existing studies, the relevant studies are shown in Table 1.

Table 1: Summary of related work

Author	Research Content	Method	Implications
Baltakys K et al. [11]	Investor behavior prediction in social networks	Graph neural network	Suitable for modeling multi-agent relationships
Kang M et al. [12]	Identification of digital resource clusters	Resource clustering analysis framework	Can be used to divide collaborative units of innovation factors
Guo C et al. [13]	Measurement of digital economy development index	Hierarchical data envelopment analysis	Helps quantify regional digital economy development
Wang Q [14]	Explainable digital economy decision-making	Uncertain-weight decision model	Supports interpretation of ecosystem construction outcomes
Hansen H F et al. [15]	Hierarchical identification of artificial intelligence diffusion	AI capability maturity model	Can characterize differences in the intelligence level of participating entities
Breiter K et al. [16]	Evolution of ambidextrous transformation capability	Dynamic capability maturity modeling	Indicates that ecosystem evolution is stage-based
Basole R C et al. [17]	Intelligent analysis of complex business ecosystems	AI-enabled visual analytics	Improves observability of ecosystem structures
Möller F et al. [18]	Industrial data ecosystems and data spaces	Data space organization	Supports cross-organizational data collaboration
Degen K et al. [19]	Orchestration of digital identity data ecosystems	Digital public infrastructure perspective	Strengthens institutional coordination capability
Abbas A E et al. [20]	Collaborative governance of data sovereignty	Social contract framework	Enriches the design of data-sharing rules

Moller F et al. studied industrial data ecology and data space, and proposed a data organization method supporting cross-organizational collaboration by data space [18]. This study emphasizes the basic role of standardized sharing, interface interconnection and trusted exchange in ecological collaboration. Degen K et al. studied the ecological orchestration of digital identity data from the perspective of government, and proposed the organizational function of digital public infrastructure in multi-agent collaboration [19]. This view shows that regional innovation ecology not only depends on enterprises and platforms, but also needs institutionalized data coordination mechanisms. Abbas A E et al. studied the connotation of social contract of data sovereignty and proposed a framework for understanding collaborative governance beyond data control [20]. This research expands the boundary of data governance, and provides theoretical support for data authorization, sharing rules and feedback updates in the innovation ecosystem.

In summary, the existing research has formed a relatively complete foundation in relation network modeling, resource cluster identification, index measurement, explanatory decision-making, capability maturity analysis, ecological visualization, data space organization and data governance. However, the research on Chengdu-Chongqing twin-city economic circle still needs to incorporate digital economic indicators, innovation subject relationships, cross-regional coordination units and dynamic feedback processes into the same calculation model. The existing results are mostly developed from a single perspective, and the construction process, spatio-temporal correlation expression and result feedback update of regional innovation ecology have not formed a closed loop in a unified framework. Therefore, on the basis of absorbing the above research ideas, this paper constructs an intelligent analysis model for the innovation ecology of Chengdu-Chongqing Shuangcheng, which combines multi-source heterogeneous data clustering, spatio-temporal graph neural network and dynamic correction mechanism, so as to obtain a more suitable computational expression for regional innovation collaboration. From the perspective of computer research, the above literature has shown that regional ecological analysis is shifting from empirical induction to data-driven modeling, from static index comparison to graph structure learning, and from result description to interpretable calculation and feedback regulation, which also provides a clear technical starting point for the design of the method in this paper.

3 Construction model of innovative ecological intelligence in Chengdu-Chongqing twin cities

3.1 Multi-source heterogeneous innovation factor data clustering and collaborative unit division

The innovation ecology of Chengdu-Chongqing twin-city economic circle is not linearly superimposed by a single subject, but a composite structure jointly shaped by enterprise research and development activities, university scientific research cooperation, patent transfer path, platform trading behavior, capital intervention frequency and policy support intensity. Data from different sources have obvious differences in acquisition caliber, time granularity, spatial hierarchy and index attributes. If these data are directly sent into the subsequent association modeling process, the node boundary is prone to drift, and the aggregated relationship will also entrainment more noise, which will weaken the interpretability of the innovation collaboration structure of the twin cities. In order to transform the scattered innovation elements into computable, groupable and traceable structural units, this section first unifiedly encodes the multi-source heterogeneous data, and then divides the collaborative units by clustering calculation, so that the originally scattered subjects, events and relations can form a stable boundary in the unified representation space.

In order to show the data processing logic of this section more intuitively, Fig. 1 concatenates the whole process of multi-source innovation elements from original access to collaborative unit generation. The leftmost part of the figure is the original data access layer, which contains enterprise innovation records, scientific research cooperation records, platform transaction records, capital activity records and policy support records. The middle part is the unified processing layer, which completes standardization, missing completion, temporal alignment, spatial mapping and anomaly screening in turn. On the right is the cluster generation layer, which is used to form several cooperative unit labels with common attribute boundaries, and the output is the set of nodes that can be directly called by the subsequent graph model. The arrow relationship in the figure shows that the cooperative unit is not directly obtained from a single classification, but is obtained by gradually converging in multiple rounds of iterations.

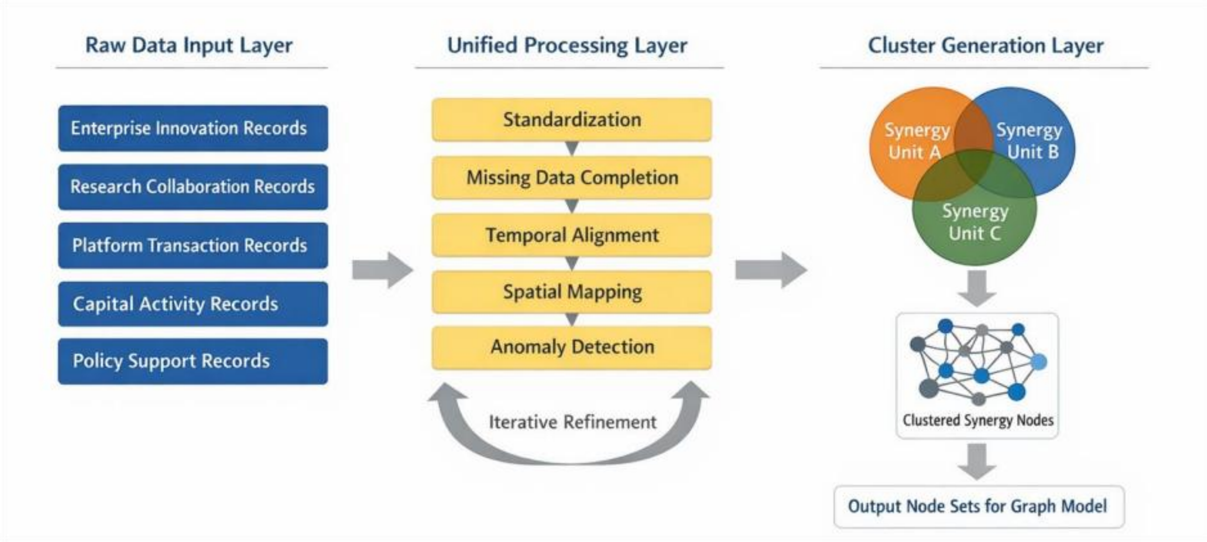

Figure 1: Flow chart of multi-source heterogeneous innovation factor data clustering and collaborative unit division

In order to uniformly write the multi-source innovation elements into the same computing space and provide a consistent data entry for subsequent standardization, distance measurement and unit division, the sample set can be defined as follows.

$$X = \{x_i \mid x_i \in \mathbb{R}^d,\ i = 1,2,\ldots,N\} \tag{1}$$

Here, x_i represents the feature vector of the i innovation subject or innovation event, d represents the attribute dimension, and N represents the total number of samples. The purpose of this expression is to push different data sources such as enterprise, platform, capital, research, and policy into the same input set, so that they can obtain a consistent representation entry for subsequent processing. Only if this layer of unification is done first, the later clustering results will be comparable and the boundaries of collaborative units will not be directly disturbed by the differences in data sources.

In order to weaken the impact of dimensional differences and extreme observations on the moving direction of the cluster center, and maintain the relative boundary relationship between different samples, the data preprocessing is completed by robust standardization. The calculation form is written as follows.

$$z_{ij} = \frac{x_{ij} - \mathrm{Med}_j}{\mathrm{IQR}_j + \varepsilon} \tag{2}$$

Here, Med_j represents the median of the j dimension feature, IQR_j represents the interquartile range, and ε is a tiny constant to prevent the denominator from being zero. After this process, the data from different sources are pulled back into the range of comparable scales, and extreme values do not dominate the clustering results. The normalized vector formed in this way is more suitable for the similarity identification of innovation subjects, and is more conducive to retaining the hierarchical differences between the three types of states of "high active, medium active and low active" in the innovation structure of the twin cities.

In order to reflect the difference in importance of different indicators in the innovation ecology in the distance calculation stage, instead of treating all attributes as equally valid, this section uses the weighted distance measurement method to measure the proximity between the sample and the cluster center, and its expression is:

$$D(x_i, c_k) = \sqrt{\sum_{j=1}^{d} w_j \left(z_{ij} - c_{kj}\right)^2} \tag{3}$$

Here, c_k represents the k cluster center and w_j represents the weight of the j dimension feature. The significance of this formula is that the indicators of knowledge flow, industry embedding, platform connection and capital response have different influence intensities in the distance calculation, so that the division of collaborative units is closer to the real organization of regional innovation ecology, rather than mechanical clustering only based on numerical values.

In order to ensure that each sample can fall into the unique collaborative unit according to the nearest neighbor principle and form a reproducible class label, the sample attribution rule is written as follows.

$$r_{ik} = \begin{cases} 1, & D(x_i, c_k) = \min_q D\,(x_i, c_q) \\ 0, & \text{otherwise} \end{cases} \tag{4}$$

Here, r_{ik} indicates whether the sample x_i is assigned to the k cluster unit. This rule ensures that an innovation subject belongs to only one closest cell in a certain iteration round, thus avoiding overlapping category boundaries. For the innovation ecological modeling of Chengdu-Chongqing Shuangcheng, such a single attribution mechanism is conducive to subsequent node mapping, because each subject has a clear structural position and will not be repeatedly included in multiple groups in the propagation stage.

In order to make the clustering center be constantly corrected with the changes of the internal members of the cell, and gradually approach the real structure center of gravity, the update method of the cell center is written as follows.

$$c_k = \frac{\sum_{i=1}^{N} r_{ik}\, z_i}{\sum_{i=1}^{N} r_{ik}} \tag{5}$$

Here, z_i represents the normalized sample vector. This updating process is not a simple arithmetic average, but a process in which the unit semantics gradually takes shape. As the internal members steadily gather, the center point will be more and more representative of the common characteristics of the unit. The cluster centers obtained in this way have not only statistical significance, but also structural significance, and can be used to express the typical position of a certain type of innovation subject in the regional ecology.

In order to judge whether the current partition result meets the requirements of closeness within units and separation between units at the same time, and provide a clear basis for the clustering to stop, the objective function can be written as follows.

$$J = \sum_{k=1}^{K} \sum_{i=1}^{N} r_{ik} \, \|z_i - c_k\|^2 + \lambda \sum_{p \neq q} \frac{1}{\|c_p - c_q\|^2} \tag{6}$$

Here, the former term measures the degree of contraction of samples inside the cell around the center, the latter term measures the degree of separation between different cell centers, and λ is the balance coefficient. This formula takes into account both internal consistency and external discriminability, so that the cooperative elements will neither be excessively loose, nor will there be boundary extrusion. This is critical for modeling innovation ecosystems, as subsequent graph propagation requires that nodes are both clearly grouped among themselves while preserving true differences in cross-group connections.

Through the above steps, the scattered innovation agents are compressed into a set of collaborative units with common attribute boundaries, consistent internal semantics, and clear external relations. Compared with the practice of directly using the original node, the method in this section can better deal with the structural differences of heterogeneous data, and make the innovation ecology of Chengdu-Chongqing transform from "data stacking" to "structural input".

3.2 Innovation ecological correlation Modeling based on Spatio-temporal graph neural Network

After completing the division of collaborative units, the key task of the innovation ecology of Chengdu-Chongqing twin cities is no longer to identify "what subjects are there", but to describe "how these subjects are related, how they evolve over time, and how they form cross-regional collaboration". The joint research and development between enterprises and universities, the resource orientation between platforms and capital, and the coupling relationship between knowledge production and industrial transformation are not linear links that exist statically, but network processes that are constantly reconstructed over time. If we only rely on annual statistics or local correlation analysis, we can only get fragmentary conclusions, which are difficult to reflect the real internal transmission mechanism of innovation ecology. Therefore, this section introduces the spatio-temporal graph neural network, regards the collaborative units as dynamic graph nodes, regards knowledge flow, industry flow, capital flow and policy response as multi-type edges, and learns the correlation strength and evolution state of innovation ecology in a unified graph structure.

To more clearly illustrate how collaborative units accomplish association modeling in the graph structure, Fig. 2 shows the complete process from node generation, relation mapping, timing propagation to global convergence. The left side of the figure is the input layer, which receives the collaborative unit labels formed in the previous section and their attribute vectors. The middle part is the dynamic graph construction layer, which generates the relationship matrix in each time window, and writes the industrial collaboration, knowledge connection, capital interaction and policy coupling into the edge weight. Then it enters the propagation layer, where the graph convolution is responsible for the neighborhood feature absorption, the time update unit is responsible for retaining the diachron-based evolution trajectory, and the attention aggregation layer is responsible for highlighting the structural contribution of key nodes. The rightmost output is the global state representation of regional innovation ecology, which is used to support subsequent correction and feedback update.

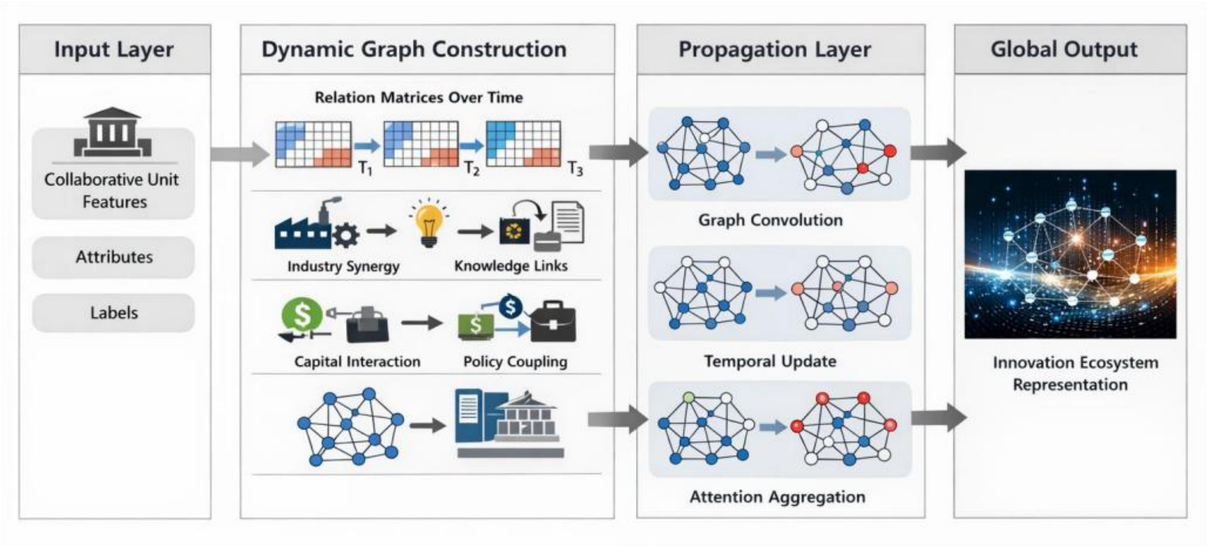

Figure 2: Framework diagram of innovation ecology correlation modeling based on spatio-temporal graph neural network

In order to represent the structural changes of Chengdu-Chongqing innovation ecology in continuous time Windows in a unified way, and to establish dynamic calculation boundaries for relationship propagation, the regional innovation graph can be expressed as follows.

$$G_t = (V_t, E_t, A_t), \quad t = 1,2, \dots, T \tag{7}$$

Here, V_t represents the set of nodes At time t, E_t represents the set of relations, and A_t represents the weighted adjacency matrix. This definition formally incorporates the time dimension into the graph structure, so that the innovation ecosystem is no longer regarded as a static network with a single section, but as a dynamic graph that can be continuously observed. For this task, this means that the synergy between the two cities can be tracked hour by hour over time, rather than being compressed into an average result.

In order to fuse multi-source innovation relations into a unified edge weight and maintain the distinguibility of different relationship sources in the calculation, the construction method of edge weight is written as follows.

$$a_{ij}^t = \alpha s_{ij}^t + \beta k_{ij}^t + \gamma f_{ij}^t + \delta p_{ij}^t \tag{8}$$

Here, s_{ij}^t represents the strength of industrial synergy,k_{ij}^t represents the strength of knowledge flow,f_{ij}^t represents the strength of capital interaction, p_{ij}^t represents the strength of policy coupling, and $\alpha,\beta,\gamma,\delta$ are the learnable coefficients. The key point of this expression is not the summation itself, but to compress the multi-type relations into the same side weight space, while preserving the different contributions of each kind of relation to the final connection strength. The edge weights obtained in this way can not only carry on the real network connections, but also avoid the excessive dominance of a single relationship in the propagation result.

In order to make the node representation not only contain its own attributes, but also carry time location and region location information, the initial node embedding is defined as follows.

$$h_i^{(0,t)} = W_0\,[z_i^t \| u_i^t \| m_i^t] \tag{9}$$

Here, z_i^t represents the node attribute vector, u_i^t represents the temporal encoding, m_i^t represents the spatial identity embedding, and W_0 is the mapping matrix. This formula enables each node to carry three types of information at the same time, including attribute, time and space, before entering the propagation phase. For the innovation ecology of the twin cities, this point can avoid the situation that "similar subjects are misjudged as the same state in different regions", and make the graph network more sensitive to identify the different collaborative patterns between Chengdu and Chongqing.

In order to absorb the structural information of surrounding nodes in the neighborhood propagation stage and let the local synergy relationship enter the current node representation, the graph convolution update relationship is written as follows.

$$h_i^{(l+1,t)} = \sigma\left(\sum_{j\in N(i)} \hat{a}_{ij}^t W_l h_j^{(l,t)}\right) \tag{10}$$

Here, $N(i)$ represents the neighborhood set of node i, $\hat{a}_{ij}^t$ represents the normalized edge weight, W_l represents the parameter matrix of the l layer, and σ represents the nonlinear activation function. This formula reflects the process of "local relation entering node state". Nodes are no longer defined only by their own attributes, but constantly absorb the structural information of the surrounding innovation agents, so as to form a representation result that is more in line with the real innovation network.

In order to enhance the model's ability to distinguish key connections and make the propagation process pay more attention to high-value nodes and high-strength edges, this section further introduces the relationship attention calculation, which is of the form:

$$\theta_{ij}^t = \frac{\exp\left(\phi^\top[h_i^{(l,t)} \| h_j^{(l,t)}]\right)}{\sum_{q\in N(i)} \exp\left(\phi^\top[h_i^{(l,t)} \| h_q^{(l,t)}]\right)} \tag{11}$$

Here, ϕ is the learnable parameter vector and θ_{ij}^t represents the attention weight of node i to its neighborhood node j. The function of this formula is to dynamically assign the propagation importance of different adjacent edges, so that the knowledge core nodes, capital hub nodes and platform connection nodes are automatically highlighted in the structural modeling, so as to improve the fineness of ecological correlation expression.

In order to retain the historical state in the continuous time window and avoid the stage changes of the innovation ecology to be truncated in the single-step propagation, the temporal state update is written as follows.

$$q_i^t = \rho q_i^{t-1} + (1-\rho)\tilde{h}_i^{(L,t)} \tag{12}$$

Here, q_i^t represents the temporal state of the node at time t, ρ is the memory retention coefficient, and $\tilde{h}_i^{(L,t)}$ represents the graph representation of the last layer after combining the attention weights. This formula preserves the continuity in time, so that the innovation ecology can not only reflect the current connection, but also reflect the previously accumulated collaborative inertia. For regional innovation research, this diachronic memory is closer to the real evolution process than a single section.

In order to compress the evolution results at the node level into ecological states at the regional level and provide a unified input for subsequent feedback updates, the global state aggregation relationship is written as follows.

$$g_t = \sum_{i \in V_t} \omega_i^t q_i^t \tag{13}$$

Here, ω_i^t represents the global contribution weight of the node at time t, and g_t represents the overall state vector of the regional innovation ecology. This formula completes the transformation from "node relationship expression" to "regional ecological expression", so that the local propagation results can finally fall on the overall collaborative structure of the two cities, and provide a compact and continuous state basis for the dynamic correction and feedback update in the next section.

After the above process, the multi-type relationships between collaborative units are uniformly written into the dynamic graph structure, and the local neighborhood propagation, key connection identification and time series state accumulation together constitute the association modeling process of regional innovation ecology. Compared with conventional static regression or simple network indicators, the method in this section is more suitable for dealing with multi-agent interaction and cross-regional collaborative expression under the background of digital economy, and also makes the innovation ecology of Chengdu-Chongqing cities further move from relationship description to structure learning and state evolution analysis.

3.3 Dynamic correction and feedback update mechanism for ecological construction

The spatio-temporal graph neural network can output the structure state of the innovation ecology of Chengdu-Chongqing, but the regional innovation activities are not uniformly carried out under ideal conditions. The change of policy rhythm, the adjustment of platform rules, the transfer of capital preference, and the shock of industrial chain events will cause the periodic deviation between the model output and the real observation. If there is no correction mechanism, the structural errors in the early propagation will accumulate in continuous time Windows, and eventually affect the stability of the construction effect evaluation. To this end, this section designs a dynamic correction and feedback update mechanism for ecological construction, and writes the observation results, residual changes and structural states back to the model, so that the innovation ecological analysis forms a closed-loop process of "generation-control-correction-re-propagation".

To make this closed-loop process more intuitive, Fig. 3 illustrates the processing path from ecological result generation to residual reflux. In the figure, the far left is the regional global state output by the previous section, the middle is the result generation and observation control module, and the right is the residual screening, gated control and state writeback module. The flow illustrates that, rather than appending a patch to the result, dynamic correction pushes the error back into the structure layer, so that node states, relationship weights, and global representations are continuously corrected with observations.

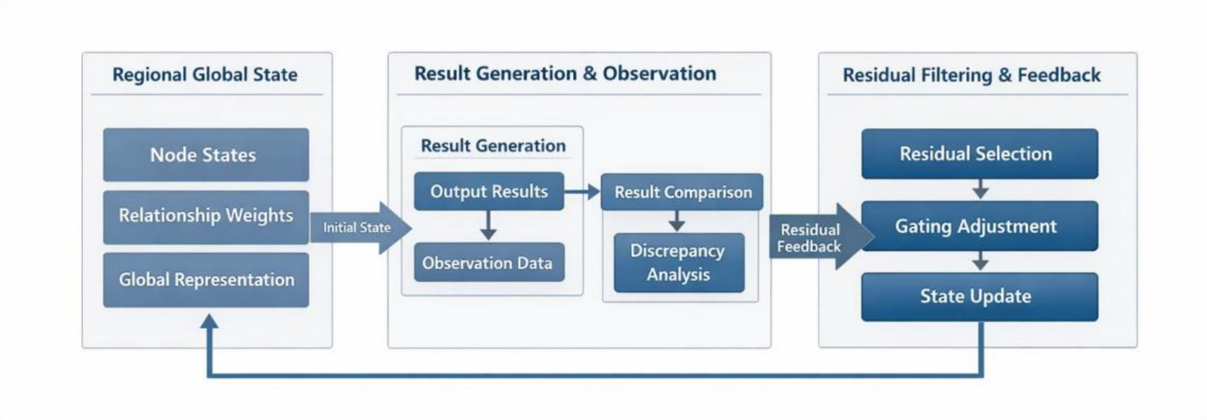

Figure 3: Graph of dynamic correction and residual reflux mechanism

In order to express the difference between the model output and the real observation explicitly and provide a clear quantitative basis for subsequent correction, the residual term is defined as follows.

$$e_t = y_t - \hat{y_t} \tag{14}$$

Here, e_t represents the overall deviation at time t, y_t represents the true observed value, and $\hat{y_t}$ represents the model output value. This expression, while concise, acts as the starting point for a feedback chain. Only when the deviation is explicitly written out first can the subsequent gating adjustment and state writeback become directional, and the model can know in which direction to shrink.

In order to avoid excessive correction caused by short-term fluctuations and make the correction amplitude change automatically with the structure state, the correction intensity is generated by gating method, and its calculation form is written as follows.

$$\eta_t = \sigma(W_e[e_t \| g_t] + b_e) \tag{15}$$

Here, g_t represents the global state vector at the current time, W_e and b_e are learnable parameters, and η_t represents the correction strength. The significance of this formula is that the deviation size and the current structure state are jointly included in the judgment, so that the feedback update considers not only the result error, but also the overall stability degree of the current ecological structure. In this way, the system will not frequently perturb the global state due to local fluctuations, and truly persistent deviations will not be ignored.

In order to write the correction signal back to the state representation of regional innovation ecology and complete the reverse correction from "result layer to structure layer", the update relation is written as follows.

$$\tilde{g}_t = g_t + \eta_t \odot e_t \tag{16}$$

Here, $\tilde{g}_t$ represents the corrected global state and $\odot$ represents the element-wise action. This formula realizes the core action of feedback update, that is, on the basis of retaining the original structure backbone, the observation deviation is written back to the system in a controlled way. After this process, the model output will gradually approach the true innovation ecological state, and the learned structural relationship will not be destroyed by a single adjustment.

To further illustrate how the feedback update operates in the structural layer, Fig. 4 shows how the correction signal flows back from the global state to the critical nodes and edges. In the graph, high deviation regions are identified according to the corrected global state, and then the local parameters are corrected by combining the node contribution and edge strength. Finally, the new ecological construction results are output. The writeback path in the figure emphasizes that the feedback update is not a single point of repair, but a continuous expansion along the three levels of "global-node-edge weight", which can ensure that the correction results of the innovation ecology are both directional and structural consistent.

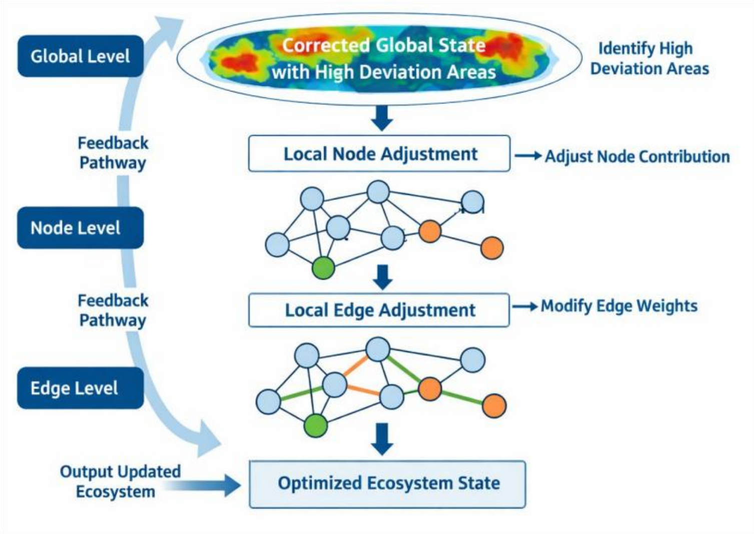

Figure 4: Flowchart of node state revaluation driven by feedback update

In order to make the dynamic correction and feedback update process clearer in engineering implementation and form a continuous flow with the clustering and association modeling stages of the previous two sections, Table 2 shows the operation steps of the mechanism in this section.

Table 2: Dynamic correction and feedback update process

Step	Processing Content
1	Read the regional states and node representations output by the spatiotemporal graph neural network
2	Generate ecosystem construction results and compare them with real observations
3	Compute the residuals and generate correction intensity
4	Write the correction signals back to the regional states and key node representations
5	Adjust edge weights and propagation parameters to form a new structural representation
6	Output the updated ecosystem construction results and proceed to the next round of evaluation

Through this mechanism, the result of innovation ecological construction is no longer a one-time output, but a dynamic result with continuous correction ability. The system can continuously adjust its own structure expression according to real observation, so that the innovation ecological analysis of Chengdu-Chongqing is closer to the real changes in the digital economy scene. Compared with the static result verification, this method is more suitable to deal with the stage fluctuation and structure deviation in cross-region collaboration, and also makes the intelligent construction model proposed in this paper have stronger adaptability, stability and engineering usability.

4 Analysis of innovative ecological construction results of Chengdu-Chongqing twin cities

4.1 Research data selection and preprocessing

In order to ensure a stable data basis for the analysis of the innovation ecological construction results of the Shuangcheng Economic Circle in Chengdu-Chongqing region, this paper adopts the multi-source data selection scheme for regional innovation collaboration, and the sample range covers 38 districts and counties in the Shuangcheng economic Circle in Chengdu-Chongqing region. The data sources include national public data on intellectual property rights, enterprise annual reports and industrial and commercial registration information, high-tech enterprise directory, scientific research project filing information, technology contract transaction records, industrial investment event records, government open data platform and statistical data of key industrial parks. The data from different sources correspond to six types of information, namely, knowledge output, subject activity, capital flow, platform connection, policy support and spatial distribution, so that enterprises, universities, research institutions, platform organizations and government support nodes in the innovation ecosystem can be expressed under the unified computing framework.

In the original sample collection stage, this paper firstly uses the unified social credit code, organization name and administrative division code as the cross-table association primary key to merge and verify the duplicate subjects, homomorphic and heterogenous subjects and mismatched records. Then, multi-source event alignment is completed according to the event number, spatial positioning information and business correlation field, so that records such as patent transfer, joint research and development, investment entry and policy response can be mapped to the same structural window. For the continuous variables with low missing ratio, the group median was used to complete. For records with incomplete category fields, the consistency was repaired by combining upstream and downstream relationships and historical labels. For abnormally high value samples, the combination of quantile truncation and manual spot check was used to complete the screening. After this process, the data noise is obviously compressed and the statistical caliber among heterogeneous sources is also unified.

In order to more clearly explain the composition of the data used in this section, the main data types, field contents and preprocessing methods are shown in Table 3.

Table 3: Research data sources and preprocessing methods

Data Type	Main Fields	Data Role	Preprocessing Method
Patent and Research Collaboration Data	Number of patent applications, number of technology transfers, number of joint projects	Characterize knowledge flows and innovation output	Deduplication, temporal alignment, institution matching
Enterprise and Industrial Operation Data	Enterprise size, R&D investment, revenue growth rate	Characterize entity activity and industrial embedding	Standardization, missing value imputation, anomaly screening
Investment and Platform Interaction Data	Financing rounds, investment amount, platform connection frequency	Characterize capital flow and platform collaboration	Event encoding, relationship mapping, weight compression
Policy and Regional Support Data	Fiscal support, park carriers, regional level	Characterize institutional response and spatial support	Unified administrative coding, category correction, normalization

In the model input construction phase, all indicators are uniformly mapped into three types of variables: node attribute vector, edge attribute vector and structure label. Continuous features are processed by robust normalization, discrete features are compressed by embedding coding, and high-dimensional relation items are stored in the form of sparse matrix to reduce the storage burden in the graph modeling stage. The effective sample formed finally covers 38 districts and counties in Chengdu-Chongqing Shuangcheng economic Circle, and contains a total of 42318 innovation event records. On this basis, the core innovation subject nodes and cross-subject association edges are generated, which provide a unified input for subsequent clustering, graph propagation and feedback update. The training, validation, and test sets were partitioned by 7:1:2 and the structure distribution was kept consistent to avoid local sample bias.

4.2 Build model performance comparison experiment

To verify the applicability of the proposed model in the innovation ecology construction task of Chengdu-Chongqing twin cities, four types of comparison methods are set in this section, which are MLP-Eco, GCN-Eco, STGNN-Eco and the full model proposed in this paper. The experiment uses a unified data partition method and the same training environment, and the evaluation metrics include construction accuracy, collaborative recall, structure F1 value, false positive rate and AUC. The training platform uses Intel Xeon Gold 6226R processor, NVIDIA V100 graphics card and 128 GB memory. The software environment is Python 3.8, PyTorch 1.10 and DGL 0.9. AdamW was used as the optimizer with an initial learning rate of 0.001, a batch size of 64, a maximum training round of 180, and a fixed random seed of 42.

In the overall performance comparison stage, the average construction accuracy of the complete model on the test set reaches 93.4%, the collaborative recall rate is 91.7%, and the structural F1 value is 92.5%. The overall performance is stably better than the other three methods. The average construction accuracy of MLP-Eco is 87.9%, GCN-Eco is 90.2%, and STGNN-Eco is 91.6%. In order to compare the relative differences of the four methods on different indicators more intuitively, Fig. 5 shows the comprehensive indicator thermal results. It can be seen in the figure that the color distribution of the full model in the three dimensions of construction accuracy, collaborative recall and structural F1 value is more concentrated, indicating that it has less fluctuation on different test subsets, while the color in the false alarm rate dimension is significantly lighter, indicating its better false alarm control ability.

Figure 5: Heat maps of the four model comprehensive indicators

Fig. 5 shows that the recognition results of the full model on high-density collaborative samples and cross-region boundary samples are more stable, and the average false alarm rate is controlled at about 4.1%, which is significantly lower than 7.4% of MLP-Eco, 5.8% of GCN-Eco and 4.9% of STGNN-Eco. This shows that it is still difficult to cover the heterogeneous relationships in complex innovation networks by only relying on static features or simple graph propagation, and the addition of collaborative unit division and feedback update makes the model more reliable in dealing with boundary connection and weak correlation samples.

To observe the model's balanced relationship between precision and recall, Fig. 6 illustrates the PR curves of the four methods. The average precision of the complete model reaches 0.936, which still maintains a relatively stable curve trend in the high recall interval. The average accuracy of STGNN-Eco is 0.902, GCN-Eco is 0.881, and MLP-Eco is only 0.842. In the figure, the curve of the complete model is generally at the top, indicating that the accuracy is not significantly sacrificed while the coverage of the positive class is expanded.

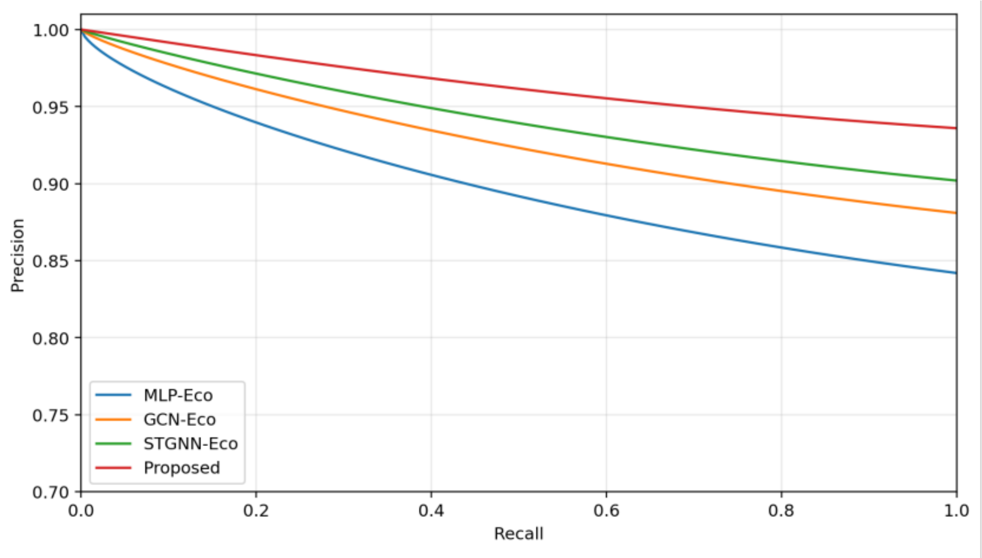

Figure 6: Comparison plots of the PR curves of the four models

The results of PR curve show that the full model has a good ability to distinguish between high collaboration nodes and medium and weak collaboration nodes, especially when the recall rate is close to 0.90, it can still maintain a high precision. This result shows that multi-source clustering and spatio-temporal propagation together improve the sample representation quality, while the dynamic correction mechanism further compresse the misjudgment accumulation.

In order to test the ability of the four methods to distinguish between positive and negative samples from the perspective of overall discrimination, Fig. 7 shows the corresponding ROC curves. The average AUC of the complete model is 0.947, which is higher than 0.928 of STGNN-Eco, 0.902 of GCN-Eco and 0.861 of MLP-Eco, indicating that the model in this paper has stronger overall discrimination ability in the identification of innovation synergy relationships.

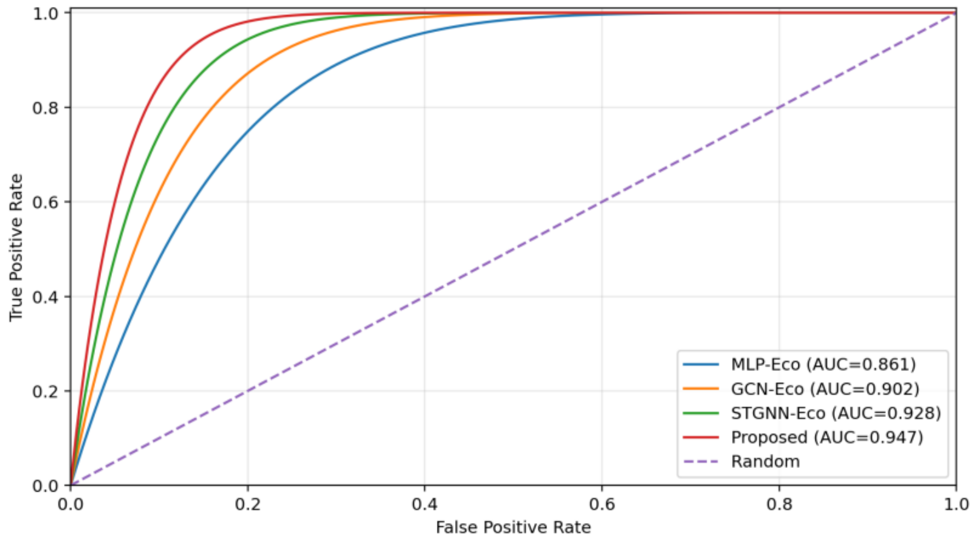

Figure 7: Comparison plots of ROC curves for the four models

Fig. 7 shows that the curve of the full model is closer to the upper left corner, and a higher true rate can be obtained at a lower false positive rate, indicating that it can not only identify the core synergy relationship, but also distinguish the non-synergy connection more effectively. In contrast, MLP-Eco and GCN-Eco show weak discrimination on boundary samples, and the output is more susceptible to local noise interference.

To compare the error distributions of different models on the test set, boxplots are used in Fig. 8 to show the relative error structures of the four methods. The median error of the full model is 3.8%, which is the most concentrated error interval and the least number of outliers. The median error of STGNN-Eco is 5.1%, GCN-Eco is 6.3%, and MLP-Eco reaches 8.2%.

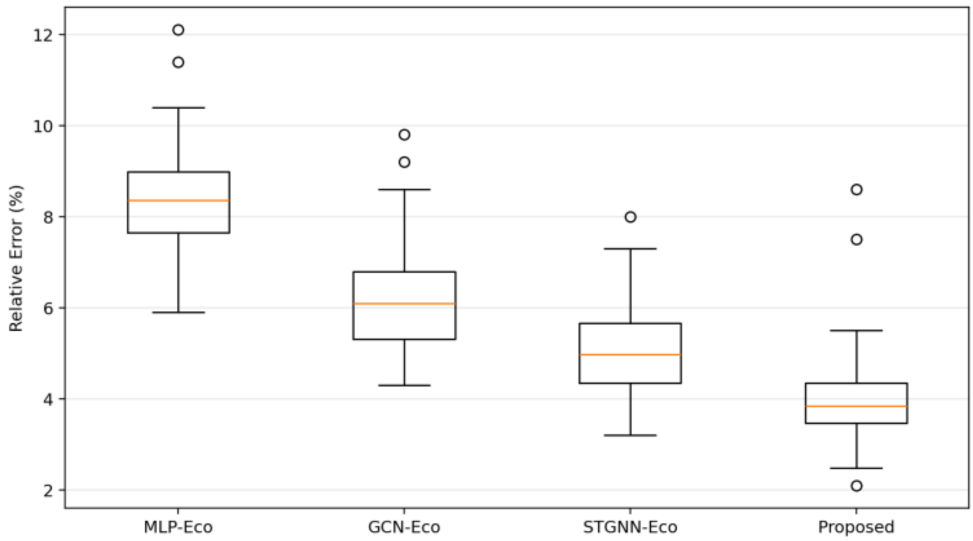

Figure 8: Box plots of test errors for the four models

Fig. 8 shows that the full model not only has lower average error, but also has better stability on local high bias samples. This shows that the feedback update mechanism effectively suppresses the error amplification in the cross-region boundary nodes and weak ties samples, and makes the output more suitable for the subsequent regional collaborative verification.

To illustrate the convergence in the training phase, Fig. 9 shows the loss change curves of the four models on the validation set. The complete model enters the stable convergence zone after the middle period, and the final loss is the lowest. STGNN-Eco is next, while GCN-Eco and MLP-Eco show relatively obvious fluctuations.

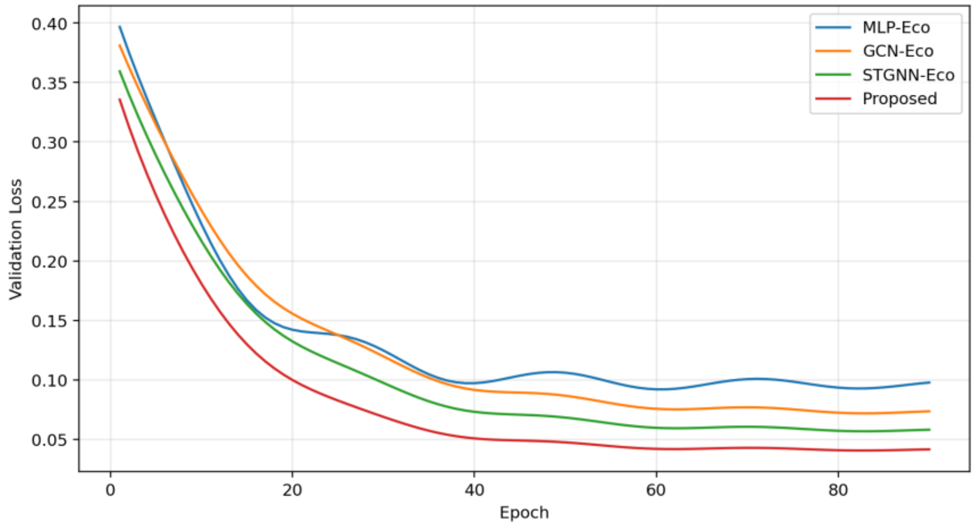

Figure 9: Validation loss convergence plots for the four models

Based on the above results, it can be seen that the complete model is superior to the comparison methods in terms of construction accuracy, recall rate, structural F1 value, false alarm rate and AUC, and has a more balanced performance in training stability and error control. It shows that the combination of collaborative unit division, spatio-temporal graph propagation and dynamic feedback update is more suitable for dealing with the multi-agent relationship, cross-regional diffusion and structural evolution process in the innovation ecology of Chengdu-Chongqing twin cities.

4.3 Evaluation of innovative ecological construction effect and verification of synergy effect of Chengdu-Chongqing Economic Circle

After the performance comparison of the model, this paper further maps the model output to the real innovation network of Chengdu-Chongqing Shuangcheng economic circle, and tests its construction effect and collaborative identification ability at the regional level. The evaluation objects covered 38 districts and counties, and were divided into three categories according to innovation density, industrial embedding degree and knowledge connection strength: core leading area, collaborative diffusion area and undertaking linkage area. The evaluation content includes the effect of structure recovery at the regional level, the ability to identify key cross-regional connections, and the impact of key modules on the overall results.

To illustrate the adaptation of the model on different region types, Table 4 summarizes the construction accuracy, collaborative recall, structural F1 value, and false alarm rate of the three types of regions. The results show that the construction accuracy of the core leading area is 94.2%, the collaborative diffusion area is 93.1%, and the connection linkage area is 92.4%. There is little difference between the three types of areas, indicating that the model is not only sensitive to the central node, but also can deal with the collaborative relationship between peripheral nodes and bridge nodes more stably.

Table 4: Results of innovation ecology construction on different regional types

Regional Type	Construction Accuracy / %	Collaborative Recall / %	Structural F1 / %	False Positive Rate / %
Core Leading Area	94.2	92.8	93.5	3.7
Collaborative Diffusion Area	93.1	91.4	92.2	4.2
Linkage Receiving Area	92.4	90.9	91.6	4.8

It can be seen from Table 4 that the core area still maintains the highest level, but there is no gap between the diffusion area, the acceptance area and the core area, which indicates that the innovation ecology of Chengdu-Chongqing Shuengcheng has a network structure that is transmitted outward from the core area, rather than relying on a few central nodes to support it alone.

In order to further test the resilience of the model to key cross-district links, Table 5 lists several representative innovation link pairs, including key passages such as Chengdu High-tech Zone -Liangjiang New Area, Tianfu New Area -Chongqing High-tech Zone of Western Science City, and Deyang-Chongqing Beibei, and compares the deviation between the predicted synergy strength and the actual observed value. The results show that the deviation of the links in each group is controlled within 0.03.

Table 5: Validation results of synergy effects for key cross-district links

Connection Pair	Predicted Collaboration Strength	Actual Collaboration Strength	Deviation
Chengdu High-Tech Zone — Liangjiang New Area	0.94	0.96	0.02
Tianfu New Area — Western Science City Chongqing High-Tech Zone	0.91	0.93	0.02
Deyang — Chongqing Beibei	0.83	0.86	0.03
Chengdu High-Tech Zone — Mianyang Science and Technology City	0.88	0.90	0.02
Liangjiang New Area — Yibin	0.81	0.84	0.03
Tianfu New Area — Deyang	0.79	0.82	0.03

Table 5 shows that the proposed model can not only identify the strong connections between dual-core regions, but also recover the medium-strength connections extending from the core region to the secondary nodes, indicating that what the model learns is not an isolated high value, but a relatively complete regional synergy path.

In order to show the collaborative gradient between districts and counties more intuitively, Fig. 10 shows the thermal results of innovation coupling strength between key nodes. In the figure, the synergy intensity between Chengdu High-tech Zone and Liangjiang New Zone is the highest, reaching 0.96. 0.93 in Tianfu New District and Chongqing High-tech Zone in Western Science City; Chengdu High-tech Zone and Mianyang Science and Technology City are 0.90. In addition to the dual-core connection, the strength between nodes in Deyang, Yibin, and Beibei and the core area also generally remains above 0.80, indicating that the secondary connection in the diffusion zone is also strong.

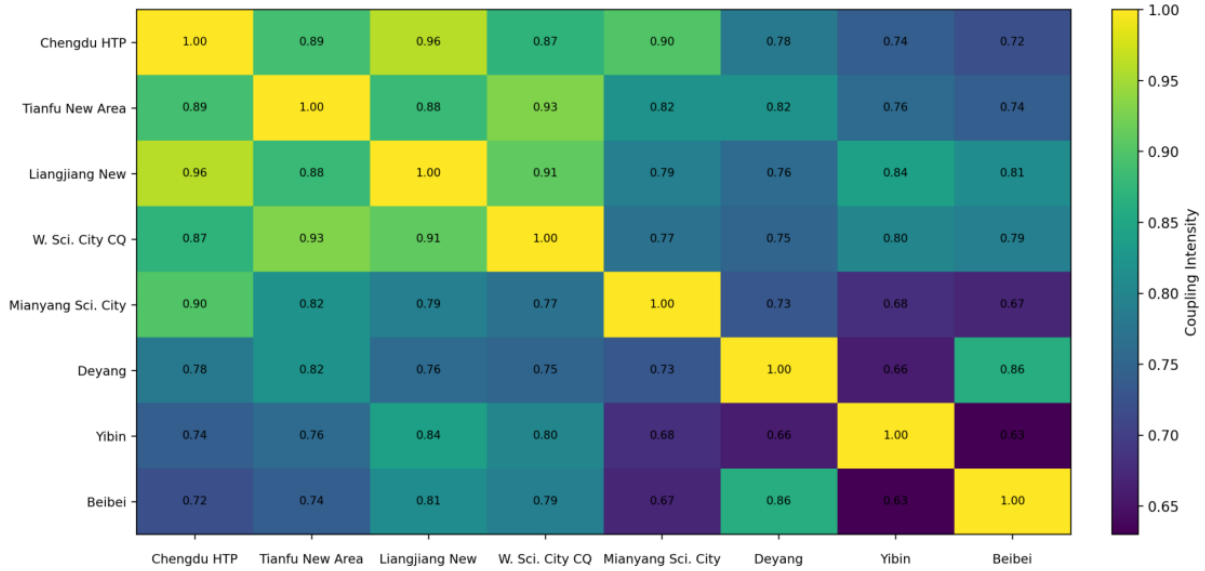

Figure 10: Heat map of innovation coupling strength in key districts and counties

Fig. 10 further shows that the innovation ecology of Chengdu-Chongqing Shuancheng has formed a structural level of progressive conduction from the core area to the diffusion area and then to the carrying area. The thermal distribution does not show a large area of fracture zone, but shows a continuous gradient change, which is more consistent with the real path of technology transfer, industrial support and scientific research cooperation.

In order to analyze the influence of each component of the model on the final results, this paper further designs an ablation experiment to remove the collaborative unit division, spatio-temporal propagation, and dynamic correction and feedback update modules respectively, and the results are shown in Table 6. It should be pointed out that the module contribution is examined here and is not repeated with the previous regional effect evaluation.

Table 6: Results of model ablation experiments

Model Version	Construction Accuracy / %	Collaborative Recall / %	Structural F1 / %	False Positive Rate / %
Full Model	93.4	91.7	92.5	4.1
Without Collaborative Unit Partitioning	90.8	89.5	90.1	5.7
Without Spatiotemporal Propagation	91.2	88.6	90.4	5.4
Without Dynamic Correction and Feedback Update	91.7	89.8	89.9	6.1

Table 6 indicates that all three part designs contribute directly to the final results. After removing the cooperative unit division, the construction accuracy decreased most obviously, indicating that the structural noise would directly enter the subsequent propagation process if the heterogeneous nodes were not compressed. After removing the spatio-temporal propagation, the collaborative recall rate decreases most obviously, which indicates that time continuity plays an obvious role in the identification of innovation links. After removing the dynamic correction and feedback update, the false positive rate increases most obviously, which indicates that the feedback mechanism plays a key role in compressing the local bias and stabilizing the output results.

Based on the above, it can be seen that the proposed model is not only superior to the comparison methods in terms of overall indicators, but also able to restore the hierarchical structure, cross-regional connection and diffusion path of innovation ecology in real regional networks. For Chengdu-Chongqing twin-city economic circle, such results can provide more detailed quantitative support for innovation resource allocation, cross-regional platform linkage, technology transfer corridor identification and key node cultivation, and also show that the intelligent construction path proposed in this paper has strong regional interpretation ability and engineering applicability.

5 Discussion

Compared with the existing research on digital economy, the characteristic of the model in this paper is not the expansion of a single index, but the integration of multi-source innovation factor organization, spatio-temporal correlation learning and dynamic feedback correction into the same calculation system. The collaborative unit division compresses the heterogeneous noise among enterprises, universities, platforms, capital and policy data, so that the regional innovation subject no longer enters the model in the form of discrete points. The spatio-temporal graph neural network retains the continuous structure of knowledge flow, industry embedding and cross-regional linkage, so that the innovation ecology of Chengdu-Chongqing Shuangcheng can be expressed as a dynamic graph that can be propagated, accumulated and updated. Experimental results show that the model is superior to the comparison methods in terms of construction accuracy, collaborative recall rate, structural F1 value and false alarm rate control, indicating that there is a stable coupling relationship between clustering, propagation and feedback. Compared with the methods that only rely on static features or single-layer graph convolution, the proposed method is more suitable for dealing with innovation networks with uneven density of agents, complex boundary connections, and obvious spatial gradients in the bi-city economic circle. At the same time, the model is still affected by the degree of data caliber unification, the integrity of cross-platform records, and the accuracy of region labeling. Especially in the linkage area, the number of weak ties samples is large, and the structural contribution of local nodes is easy to shift with the fluctuation of events. Therefore, the dynamic update threshold still needs to be optimized according to the scene. From the perspective of computer implementation, this work shows that the analysis of regional innovation ecology should not stop at static statistical comparison, but should turn to the technical path of structural modeling, relational learning and result writeback promotion, which also provides quantitative support for resource allocation, channel identification and collaborative scheduling in the innovation governance of twin cities.

6 Conclusions

Focusing on the task of promoting the construction of innovation ecosystem of Chengdu-Chongqing twin-city economic circle by digital economy in the era of artificial intelligence, this paper proposes an intelligent analysis path composed of collaborative unit division, spatio-temporal graph neural network modeling, dynamic correction and feedback update. The experimental results show that the complete model is superior to the comparison methods in terms of construction accuracy, collaborative recall rate, structural F1 value and false alarm rate control, indicating that the multi-source heterogeneous data organization, relationship propagation and result writeback can form a stable technical closed loop, and accurately restore the core connection, diffusion path and continuity level in the innovation ecosystem of the twin cities. The limitations of this paper are also clear. On the one hand, the sample is still dominated by open data and structured records, and the non-standardized collaborative activities of some small and medium-sized subjects have not been fully included. On the other hand, the feedback update threshold and time window length still depend on the experimental setting, and there is still parameter sensitivity in extreme fluctuation scenarios. Future research can be further promoted from three directions. First, more frequent platform interaction data, technical transaction logs and cross-domain flow records are introduced to enhance the expression ability of the model to real-time collaboration states. Secondly, self-supervised representation learning and dynamic graph compression strategies are combined to reduce the training overhead on large-scale regional networks. Thirdly, the design of interpretable mechanism is further strengthened, so that the model output can more directly serve the allocation of innovation resources, the cultivation of cross-regional nodes and the scheduling of regional governance. At the same time, regional collaborative modeling can be carried out around privacy-preserving computing and federated learning mechanism to improve the security, compatibility and deployment flexibility under multi-platform data access conditions.

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