ingegneria sismica
International Journal of Earthquake Engineering
Anno XLIII - Num. 2 - 2026

Research on the co-evolution mechanism of the chain sinking path of specialized and special new enterprises and rural revitalization driven by multimodal data

Liping Yang[1,*], *Jie Shen*[2], *Jiangnan Chen*[3] *and Jian Xiong*[3]

[1] School of Business, Jinggangshan University, Ji'an, 343009,China
[2] School of Finance and Accounting, Jiangxi Polytechnic University, Jiujiang, 332007, China
[3] Information Engineering School, Jiangxi Polytechnic University, Jiujiang, 332007, China

SUMMARY: *Rural revitalization and county industrial upgrading put forward higher requirements for the chain sinking path identification and synergy effect prediction of specialized and special new enterprises. This paper constructs a multi-modal data-driven collaborative evolution model of specialized and special new enterprise chain sinking and rural revitalization, which integrates enterprise structured data, policy text, spatial location, supply chain collaboration, rural development indicators and remote sensing auxiliary information. Transformer semantic encoding, spatial embedding, heterogeneous graph relational learning, multi-modal attention fusion and GRUN-Temporal Transformer time series prediction methods are used to realize enterprise sinking path identification, synergistic effect measure and evolution trend prediction. The experimental results show that the Accuracy of the proposed model in the chain sinking path recognition task reaches 93.8%, the F1-score reaches 92.3%, and the AUC reaches 95.1%. After full modal fusion, RMSE decreased from 0.186 to 0.121, R^2 increased to 0.914, and the proportion of true value falling into 95% confidence interval reached 93.7%. In the path optimization experiment, the comprehensive synergy effect score of the model reaches 0.89, the prediction error is reduced to 0.072, and the stability index is 0.93. The research shows that this method can improve the identification accuracy of enterprises 'sinking path and the prediction ability of rural revitalization co-evolution, and provide technical support for the digital decision-making of county industrial layout and rural revitalization.*

KEYWORDS: *Multimodal data; Specialized new enterprises; Chain sinking path; Rural revitalization of coordinated evolution*

1 Introduction

With the characteristics of high degree of specialization, strong innovation ability and outstanding industrial supporting value, specialized and new enterprises are important subjects to promote the extension of industrial chain, regional economic transformation and rural industrial upgrading. With the continuous deepening of the rural revitalization strategy, single enterprise investment, single point project implementation or short-cycle resource input have been difficult to fully support the long-term growth of the county industrial system. Enterprises have been ordered to sink to rural areas along the industrial chain, supply chain and innovation chain, and have gradually become an important path connecting urban

*yangliping@jgsu.edu.cn
https://doi.org/10.65102/is20261000 Published: 30 April, 2026

technological resources, county processing capacity, rural characteristic resources and market demand [1]. In this process, the sinking behavior of specialized and new enterprises is not only shown by spatial location transfer, but also involves multi-dimensional linkage such as industrial node embedding, technology diffusion, order collaboration, employment absorption, brand empowerment and data feedback, and its operation results will have a continuous impact on rural industrial structure, farmers' income, public service carrying capacity and regional innovation ecology [2, 3]. Therefore, how to identify the chain sinking path of enterprises and describe the co-evolution relationship between it and rural revitalization have become the key issues in the study of industrial digitalization and regional governance [4].

Existing studies mostly analyze from the perspective of industrial policy, enterprise growth, rural industry integration or regional coordinated development, and discuss the mechanism of specialized and new enterprises serving rural revitalization, but there are still some limitations in the method level [5]. On the one hand, traditional studies often rely on statistical yearbooks, questionnaire surveys or single economic indicators, which are difficult to fully capture the complex relationship between enterprise operation status, industrial chain relationship, geospatial layout, policy text, market transactions and rural development quality. On the other hand, enterprise chain subsidisation has obvious spatio-temporal dynamics and network correlation. Simply using linear regression, hierarchical evaluation or static index weighting methods, it is difficult to explain the transmission process between industrial nodes, and it is also difficult to predict the long-term impact of changes in subsidisation path on the level of rural revitalization [6-8]. With the development of multimodal data acquisition, natural language processing, graph neural network, time series prediction model and intelligent optimization algorithm, multi-source data such as text, table, space, transaction, public opinion and remote sensing are incorporated into the unified computing framework, which has provided a new technical basis for enterprise sinking path identification and collaborative evolution mechanism analysis [9].

Based on this, this paper focuses on the core relationship of "the chain sinking path of specialized and special new enterprises - the co-evolution of rural revitalization", and constructs a multimodal data-driven computational analysis framework. Firstly, multi-source information such as enterprise industrial and commercial information, patent achievements, supply chain cooperation, policy texts, industrial park distribution, county economic indicators and rural development data are collected, and a unified sample library is formed through data cleaning, semantic coding, spatial matching and feature normalization. On this basis, text semantic embedding, graph structure modeling and multi-modal feature fusion methods are introduced to identify the key position, sinking direction and node connection strength of the enterprise in the industrial chain. Furthermore, combining with indicators such as rural industry development, employment absorption, resource utilization, innovation diffusion and public service improvement, a synergistic effect measurement model is constructed, and the time series prediction method is used to analyze the evolution trend of rural revitalization level under different sinking paths. This study focuses not only on the path identification accuracy of enterprise chain sinking, but also on the ability of the model to explain the change of synergistic effects and the stability of prediction.

The main contributions of this paper are reflected in the following three aspects: first, the multimodal data fusion method is introduced into the chain sinking research of specialized and special new enterprises, breaking through the problem that it is difficult to express industrial relations and policy semantics by a single structured data. Secondly, a path identification model for industrial chain network is constructed, and the chain conduction characteristics in the process of enterprise sinking are revealed through the correlation calculation between enterprise nodes, industrial nodes and rural regional nodes. Third, the synergetic effect measurement and evolution prediction method of rural revitalization should be established to evaluate the comprehensive impact of enterprise sinking from the dimensions of industry driving, technology diffusion, employment promotion and regional resilience. The research results can provide model support and data basis for specialized and new enterprises to layout county industries, local governments to optimize investment chain strategy, rural industry digital governance and regional collaborative development decision-making.

2 Theoretical basis and related research

2.1 Modeling Theory of sinking path of industrial chain driven by multimodal data

The sinking path modeling of industrial chain driven by multi-modal data is to integrate enterprise operation data, industrial chain relationship data, policy text data, geospatial data, market transaction data and rural development indicators into a unified computing framework. Through feature coding, semantic representation, relationship reasoning and dynamic prediction, the sinking path of industrial chain is modeled by the multi-modal data. Identify the path law of the extension of specialized and new enterprises to the county and rural industrial system [10]. The sinking of the industrial chain is not a simple spatial migration of enterprises, but a process of diffusion of enterprise technology, orders, equipment, talents, brands and supply chain collaboration to grassroots industrial nodes. The core of the modeling is to transform enterprise nodes, industry nodes, regional nodes and rural resource nodes into computable objects, and describe the connection strength, direction relationship and evolution trend between different nodes [11-13].

At the data level, structured data can be used to describe enterprise scale, output value, number of patents, order flow and employment absorption capacity. Text data can be used to extract semantic features in policy orientation, enterprise announcement, industrial planning and news public opinion. Spatial data can reflect enterprise layout, transportation accessibility, industrial park distribution and rural resource endowment. Transaction and collaboration data reflect the upstream and downstream relationship of enterprises in the supply chain [14]. Through multi-modal feature fusion, the information bias caused by a single data source can be reduced, so that the model has the ability of industrial relationship identification, regional matching analysis and development potential judgment at the same time.

At the algorithm level, the sinking path of the industrial chain can be represented as a heterogeneous graph structure composed of multiple types of nodes. The graph neural network can learn the potential association between enterprises, industries and regions, and identify key enterprise nodes, core supporting nodes and suitable undertaking regions. For policy text and enterprise description information, semantic models such as BERT and Transformer can be used to extract deep semantic vectors, and then integrate them with numerical features and spatial features [15, 16]. For the path change process, the time series prediction model can be combined to analyze the dynamic changes of enterprise sinking intensity, industrial coordination level and rural development state. Thus, a technical chain of "data acquisition, feature coding, relationship modeling, path identification, evolution prediction" is formed, which provides a theoretical basis for the chain sinking path analysis of specialized and special new enterprises.

2.2 Research status of the collaborative evolution of specialized and special new enterprises empowering rural revitalization

Existing research shows that enterprise digital transformation is changing the organizational coordination, resource allocation and value creation mode of small and medium-sized enterprises, which provides a technical basis for specialized and new enterprises to participate in rural revitalization. Pfister and Lehmann pointed out that the effect of digital transformation of smes is not only reflected in technology investment, but also reflected in process optimization, customer value and operational performance improvement, which provides a reference for evaluating the industrial driving effect of enterprises after sinking [17]. Szukits and Moricz emphasized that data-driven decision-making needs to be supported by analysis culture and centralized management mechanism, indicating that enterprises should rely on data capabilities to identify industrial demand, resource endowment and regional matching relationships when extending to counties and villages [18]. Nucci et al. verified the promotion effect of digital technology on the improvement of enterprise productivity, indicating that specialized and special new enterprises can promote the upgrading of rural industries through technology diffusion, process improvement and production coordination [19]. However, Nell et al also pointed out that there was a risk of technological investment being disconnected from strategic goals in the process of enterprise digitalization, suggesting that the sinking of enterprises should not stop at the level of platform construction and data collection, but also be embedded in the process of supply chain reorganization, industrial collaboration and rural resource transformation [20].

From the perspective of regional coordination, the empowerment of rural revitalization by specialized and new enterprises is an ecological evolution process with multi-subject participation. Wurth et al. proposed that research on entrepreneurial ecosystem should focus on subject interaction, resource combination and institutional environment, providing a basis for understanding the collaborative relationship among enterprises, government, farmers and service agencies [21]. Kennedy believes that community wealth creation depends on local relationship network and continuous action, indicating that whether the long-term effect of enterprise sinking can be formed depends on its connection degree with rural industrial organization, employment structure and public value [22]. Burgin et al. research on digital multilocalism shows that digital technology can weaken the space restriction between the center and periphery, and help R&D, design, operation and maintenance links extend to rural areas [23]. Gerli and Whalley pointed out that rural digital infrastructure is an important condition to narrow the urban-rural digital divide, and also the support for enterprise data exchange and the implementation of intelligent services [24].

In terms of rural digital application, Lindberg and Lundgren found that rural residents' participation in digital services is affected by living environment and use experience, indicating that enterprise technology sinking needs to pay attention to the acceptance of rural subjects [25]. Rijswijk et al. proposed a socio-cyber-physical system framework for the digital transformation of agriculture and rural areas, which provided a systematic perspective for the analysis of rural revitalization co-evolution [26]. Gaw et al. pointed out that multi-modal data fusion can improve the state identification and optimization ability of complex systems, and is suitable for describing the sinking path of enterprises and the state of rural development [27]. Sarafan et al. emphasized that knowledge sharing in supply networks would affect collaboration performance, which also indicated that specialized and new enterprises need to promote the diffusion of technology, orders and management experience to rural industrial nodes through supply chain collaboration [28]. In general, the existing research provides theoretical support for this paper, but the computational identification and co-evolution prediction of the chain sinking path are still insufficient.

3 The co-evolution model construction of the chain sinking of specialized and special new enterprises and rural revitalization driven by multimodal data

3.1 Overall model design of co-evolution between chain subsiding path and rural revitalization

In order to describe the extension process of specialized and special new enterprises along the industrial chain to county and rural areas, this paper constructs a multi-modal data-driven chain subsidence path and rural revitalization co-evolution overall model. The model takes enterprises, industrial chain links, regional nodes and rural resource units as the basic analysis objects, and integrates multi-source data such as enterprise industrial and commercial information, patent data, supply chain cooperation records, policy texts, industrial park distribution, traffic location, rural industry indicators and remote sensing spatial information into the unified computing framework. Through feature coding, heterogeneous graph modeling, path reasoning, synergistic effect measurement and time series evolution prediction, the chain sinking law of the expansion of specialized and special new enterprises from the urban innovation end and manufacturing supporting end to the county processing end, rural resources end and service application end is identified. The model emphasizes the dynamic identification ability driven by data, which not only pays attention to the enterprise's own ability and the position of the industrial chain, but also pays attention to the change of the resource undertaking conditions and revitalization status in rural areas.

In the multi-modal feature representation layer, the model encodes structured data, text data, spatial data and visual remote sensing data respectively. The structured data represent firm size, R&D intensity, order capacity and employment contribution by numerical normalization and category embedding. The deep semantics in policy orientation, enterprise announcement and industrial planning are extracted by Transformer semantic encoding. The spatial data depict the location of enterprises, transportation accessibility and rural resource distribution through geocoding and distance matrix. Remote sensing or image data are used to extract land use, industrial park morphology and infrastructure coverage features through convolutional networks. The unified representation of multimodal features is as follows:

$$u_i=\mathrm{MFA}\left(a_i^s,a_i^t,a_i^g,a_i^v\right) \tag{1}$$

where u_i represents the unified multimodal feature vector of the ith object, a_i^s represents structural features, a_i^t represents textual semantic features, a_i^g represents geospatial features, a_i^v represents visual or remote sensing features, and MFA(·) represents the multimodal fusion attention function. Through this representation, data from different sources are mapped to the same feature space, which provides an input basis for subsequent reasoning about industrial chain relationships.

In the modeling layer of industrial chain relationship, this paper constructs enterprise nodes, industrial link nodes, regional nodes and rural resource nodes as heterogeneous graphs. The edges in the graph represent relationships such as supply collaboration, technology diffusion, spatial proximity, policy matching, and resource complementarity. For the connection strength between any two nodes, the model comprehensively considers feature similarity, relationship type and spatial constraint, and the calculation formula is as follows.

$$\varepsilon_{ij}^{r}=\sigma\left(u_i^{T}M_r u_j+\beta_r\cdot\rho_{ij}\right) \tag{2}$$

Here, ε_{ij}^{r} represents the connection strength between node i and node j under the relationship type r, M_r Represents the mapping matrix corresponding to the relationship type r, β_r represents the regulation coefficient of the relationship type, ρ_{ij} represents the spatial proximity or resource complementarity score, and $\sigma(\cdot)$ represents the Sigmoid activation function. The formula can incorporate enterprise capability, industrial chain relationship and regional acceptance conditions into the calculation of edge weights, so that the identification of sinking path of industrial chain has stronger semantic interpretation and spatial constraint ability. Figure 1 shows the overall architecture of the model.

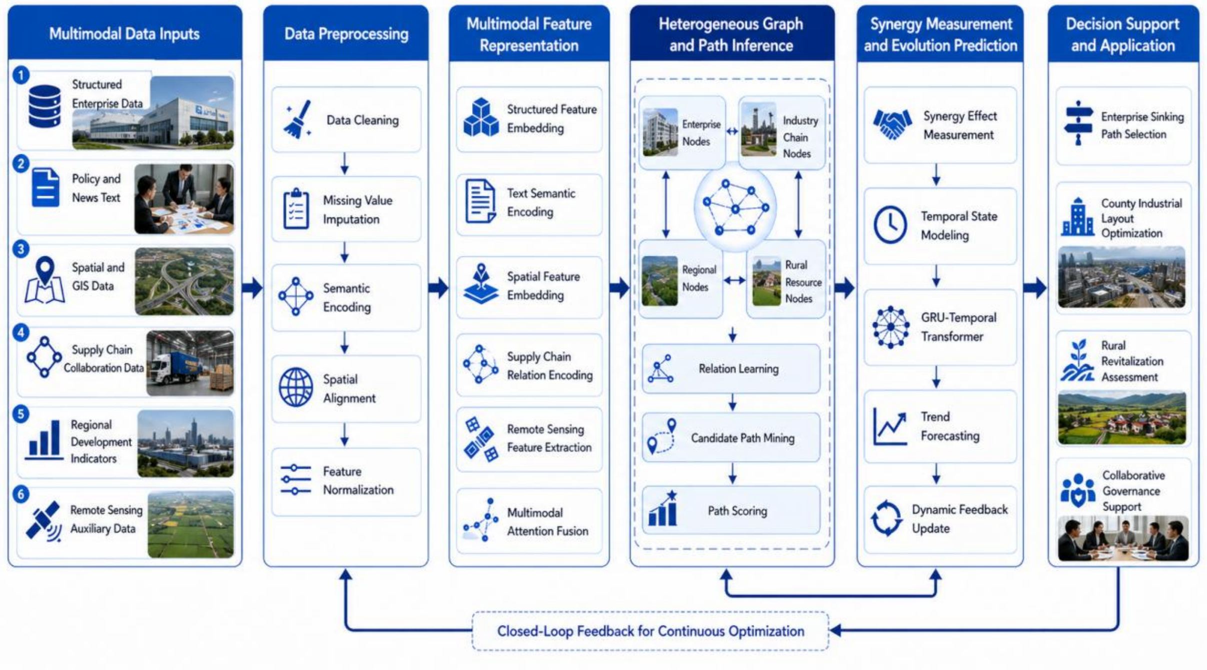

Figure 1: The overall architecture diagram of the collaborative evolution model of the chain sinking of specialized and special new enterprises and rural revitalization driven by multimodal data

In the path inference layer, the model generates candidate sinking paths based on heterogeneous graphs. Each path is composed of enterprise node, industrial chain link node, county undertaking node and rural resource node, reflecting the possible direction of enterprise extension to rural industrial system from research and development, manufacturing, supporting, processing, sales or service links. Path score comprehensively considers node connection strength, regional undertaking capacity, path collaboration cost and industry matching degree, and its calculation formula is as follows.

$$\Gamma_q=\sum\nolimits_{(i,j)\in L_q}\varepsilon_{ij}^{r}\cdot\chi_j-\lambda\cdot\Omega_q \tag{3}$$

Here, Γ_q represents the comprehensive score of the QTH candidate sinking path, L_q represents the set of edges included in the path, χ_j represents the acceptance fitness of node j, Ω_q represents the path implementation cost, and λ represents the cost penalty coefficient. The higher the score, the better the path is in terms of industrial connection, resource matching and implementation feasibility. Through the ranking of path score, the model can screen out the key chain sinking path suitable for specialized and special new enterprises to extend to rural areas.

In the co-evolution layer, the model further analyzes the dynamic influence of the sinking path of enterprises on the state of rural revitalization. The status of rural revitalization is jointly characterized by indicators such as industrial development, employment absorption, innovation diffusion, ecological resource utilization, improvement of public services and regional resilience. Considering the accumulation and lag of the sinking effect of enterprises, this paper uses the temporal state update mechanism to describe the change of regional states:

$$h_z(\tau)=\varphi\left(A_h h_z(\tau\text{-}1)+A_p\sum_{q\in Q_z}\Gamma_q\, o_q(\tau)+A_c c_z(\tau)\right) \tag{4}$$

Here, $h_z(\tau)$ represents the rural revitalization state vector of region z at time τ, $h_z(\tau-1)$ represents the state at the previous time, Q_z represents the set of sinking paths acting on region z, $o_q(\tau)$ represents the actual effect strength of path q at time τ, $c_z(\tau)$ represents the external environment and policy support vector of region. A_h, A_p, A_c represent the parameter matrices of the historical state, path action, and external environment, respectively, and $\varphi(\cdot)$ represents the nonlinear activation function. The state update mechanism can reflect the continuous impact of enterprise sinking behavior on rural development level, and provide a basis for subsequent evolution prediction and path optimization.

In general, the overall model of this paper is composed of multimodal data layer, feature representation layer, industrial chain heterogeneous map layer, path reasoning layer, collaborative evolution layer and decision-making application layer. The model enhances the expression ability of enterprises and rural nodes through multi-source data fusion, describes the industrial chain relationship through the graph neural network, filters the subsidence scheme through the path scoring mechanism, and evaluates the change of rural revitalization status through the time series update model. Finally, the closed-loop analysis framework of "data perception - path identification - effect measurement - state prediction - feedback optimization" is formed. The design can provide computer model support for the chain sinking path selection of specialized and special enterprises, the assessment of county industry undertaking capacity and the collaborative governance of rural revitalization.

3.2 Enterprise chain sinking path identification and multi-modal feature optimization method

The key of path identification for enterprise chain sinking is to extract effective features that can characterize enterprise capabilities, industrial associations, regional undertaking and rural needs from multi-source data, and transform these features into computational representations that can be used for path reasoning. In this paper, specialized and special enterprises, industrial chain links, county industrial carriers and rural resource units are uniformly abstracted as graph nodes, and supply cooperation, technology diffusion, order flow, spatial proximity, policy matching and resource complementarity are abstracted as graph edges. On this basis, a method framework of "multi-modal feature optimization-graph relational learning-chain path identification" is constructed, so that the model can automatically discover the potential path of enterprise extension to rural areas from complex industrial networks.The overall process of enterprise chain sinking path identification and multimodal feature optimization is shown in Figure 2.

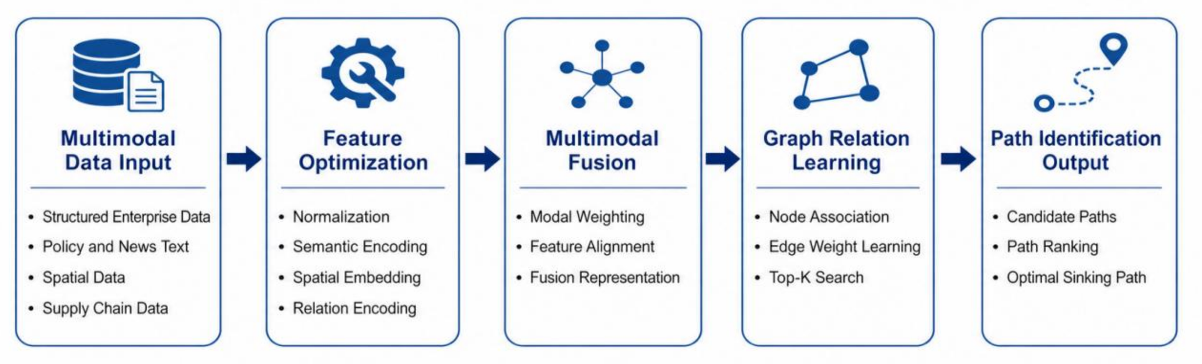

Figure 2: Flow chart of multimodal feature optimization and chain sinking path identification

In the data input stage, there are dimension differences in structured enterprise data, semantic sparsity in text data, scale inconsistency in spatial data, and missing edges and weak connections in supply chain relational data. In order to reduce the interference of data noise on path identification results, the numerical features are standardized by missing perception. The calculation formula is as follows:

$$\hat{x}_{n,p}=\delta_{n,p}\cdot\frac{x_{n,p}-\mu_p}{\sigma_p}+\left(1-\delta_{n,p}\right)\cdot\bar{x}_p \tag{5}$$

where, $\hat{x}_{n,p}$ represents the normalization result of object n on the PTH numerical feature, $x_{n,p}$ represents the original value, μ_p and σ_p represent the mean and standard deviation of the feature, $\delta_{n,p}$ represents the missing mark, and $\bar{x}_p$ represents the missing filling value. This processing can avoid model deviation caused by dimension differences of indicators such as enterprise scale, patent number and order size.

For policy documents, enterprise announcements, industry news, and investment promotion texts, we employ a Transformer encoder to extract semantic representations, so that the model can identify the implicit relationship between policy orientation, industry keywords, and enterprise development direction. The formula for calculating text semantic features is as follows:

$$q_n^{text}=\mathrm{MeanPool}\left(\mathrm{Trans}_{\theta_t}(D_n)\right) \tag{6}$$

Here, q_n^{text} denotes the textual semantic vector of object n, D_n denotes the set of texts associated with this object, $\mathrm{Trans}_{\theta t}(\cdot)$ denotes the Transformer semantic encoder with parameter θ_t, and $\mathrm{MeanPool}(\cdot)$ denotes the average pooling operation. In this way, the industry direction, policy support and technical field information in the text can be transformed into continuous vectors.

Spatial features are mainly used to describe the geographical links between enterprises and county, park, transportation nodes and rural resources. In this paper, latitude and longitude, traffic time, park distance and logistics accessibility are encoded as spatial embedding vectors, which are calculated as follows:

$$q_n^{geo}=\mathrm{ReLU}\left(B_g d_n^{geo}+b_g\right) \tag{7}$$

Here, q_n^{geo} represents the spatial embedding result, d_n^{geo} represents the geographic and traffic feature vector of object n, B_g represents the spatial mapping matrix, b_g represents the bias term, and ReLU(·) represents the nonlinear activation function. The formula can transform the spatial proximity relationship into features that can participate in depth calculation.

In order to ensure that different modalities adaptively assign weights according to their contributions in the fusion process, this paper introduces a modal reliability attention mechanism to dynamically weight structural, textual, spatial and supply chain relationship features. Modal weights are calculated as follows:

$$\alpha_{n,m}=\frac{\exp\left(c_m^T \tanh\left(G_m q_n^m\right)\right)}{\sum_{v\in M}\exp\left(c_v^T \tanh\left(G_v q_n^v\right)\right)} \tag{8}$$

Here, $\alpha_{n,m}$ represents the fusion weight of object n on modality m, M represents the set of modalities, q_n^m represents the feature vector of modality m, G_m represents the modality mapping matrix, and c_m represents the attention parameter vector. The weight can reflect the importance of various types of data for path identification in different scenarios.

After the weight calculation is completed, the model generates multimodal optimized features of the object for subsequent graph relationship learning and path search. The fusion feature is expressed as follows:

$$r_n=\mathrm{LayerNorm}\left(\sum_{m\in M}\alpha_{n,m} U_m q_n^m\right) \tag{9}$$

Here, r_n represents the multi-modal optimization feature of object n, U_m represents the dimension alignment matrix of modality m, and LayerNorm(·) represents the layer normalization function. This feature not only retains the enterprise's own capabilities, but also integrates industrial relations, spatial location and policy semantic information.

In the path identification stage, the model determines whether there is an effective sinking connection between enterprise nodes and regional nodes, industry nodes and rural resource nodes according to node characteristics and relationship types. The edge relation identification loss function is as follows:

$$J_{link}=-\sum_{(a,b,r)\in E^+}\log\ \omega_{a,b}^r-\sum_{(a,b,r)\in E^-}\log\ \left(1-\omega_{a,b}^r\right)+\tau\|\mathbf{\Theta}\|_2^2 \tag{10}$$

Here, J_{link} represents the edge relationship learning loss, E^+ represents the set of real positive sample relationships, E^- represents the set of negative sample relationships, $\omega_{a,b}^r$ represents the predicted connection probability between node a and node b under the relationship type r, τ represents the regularization coefficient, Θ represents the set of model trainable parameters. After the model is trained, the weighted industrial chain graph can be constructed according to the connection probability, and the chain sinking path of the enterprise expansion from the core industry link to the county and rural nodes can be screened through Top-K path search. The multimodal feature optimization variable configuration used in this paper is shown in Table 1.

Table 1: Multimodal feature optimization and chain sinking path identification variable configuration table

Data Category	Collected Content	Sample Size or Dimension	Encoding Method	Technical Function
Enterprise Structured Data	Registered capital, revenue range, number of patents, proportion of R&D personnel, order scale	12,846 enterprises, 42 fields	Missing-aware standardization and categorical embedding	Represents enterprise innovation capacity and industrial undertaking capability
Policy and News Text	Industrial policies, investment promotion announcements, enterprise reports, project publicity documents	52,600 text segments	Transformer semantic encoding	Extracts policy orientation and industrial matching semantics
Spatial Geographic Data	Enterprise coordinates, industrial park locations, transportation time, logistics radius	3,218 regional nodes	Geocoding and spatial embedding	Determines the spatial accessibility of enterprise sinking paths
Supply Chain Collaboration Data	Upstream and downstream cooperation, procurement and sales relationships, technical collaboration records	145,670 relational edges	Heterogeneous graph relation encoding	Identifies industrial chain connection strength and diffusion paths
Rural Undertaking Data	Industrial foundation, labor structure, infrastructure, characteristic resources	2,084 township units	Indicator embedding and normalized fusion	Evaluates the undertaking suitability of rural nodes

It can be seen from Table 1 that path identification does not rely on a single enterprise index, but integrates enterprise capabilities, text semantics, spatial location, supply chain relationships and rural undertaking conditions at the same time. This method can improve the accuracy of chain sinking path identification, and make the model more stable to find the critical path with industry driving potential and rural revitalization value in complex regional industrial networks.

3.3 Synergetics effect measurement and evolution prediction method of rural revitalization

The core of measuring the synergy effect of rural revitalization is to transform the effects of industrial drive, technology diffusion, employment absorption, resource conversion and public service improvement generated by the chain sinking of specialized and special new enterprises into calculable, comparable and predictable state variables. Based on the identification of the sinking path of enterprises and the optimization of multimodal features completed in 3.1 and 3.2, this paper further constructs the measurement and evolution prediction method of rural revitalization synergy effect. This method takes rural regional unit as the analysis object, takes industrial development, innovation diffusion, employment quality, infrastructure, ecological resource utilization and regional resilience as the main dimensions, and integrates the effect strength of enterprise sinking path, regional carrying capacity and time change trend into the model. The calculation process of "synergistic effect measurement - time series state modeling - future trend prediction - path feedback adjustment" was formed.

In the index processing stage, the sources of indicators related to rural revitalization are complex, including structured indicators such as output growth rate, employment number, and number of enterprise cooperation projects, as well as unstructured information such as policy support texts, industry news, project publicity and remote sensing identification results. In order to ensure that different indicators can enter the unified measurement space, this paper uses the interval normalization method to deal with regional indicators, and its calculation formula is as follows:

$$\vartheta_{g,k}=\frac{\xi_{g,k}-\min(\xi_k)}{\max(\xi_k)-\min(\xi_k)+\epsilon} \tag{11}$$

Here, $\vartheta_{g,k}$ represents the standardized result of region g on the KTH rural revitalization index, $\xi_{g,k}$ represents the original index value, $\min(\xi_k)$ and $\max(\xi_k)$ represent the minimum and maximum value of the index in all regions respectively, and ϵ is a small constant to prevent the denominator from being zero. The processing can eliminate the dimension difference of different indicators, so that the industry, employment, ecology and service indicators can be jointly calculated in the same model.

In the measurement stage of synergy effect, this paper introduces the dimensional attention mechanism to dynamically judge the contribution differences of different rural revitalization dimensions in the process of enterprise chain sinking. Dimension weight is calculated as follows:

$$\pi_{g,k}=\frac{\exp\left(s_k^T \mathrm{GELU}\left(R_k\vartheta_g\right)\right)}{\sum_{l\in K}\exp\left(s_l^T \mathrm{GELU}\left(R_l\vartheta_g\right)\right)} \tag{12}$$

Here, $\pi_{g,k}$ represents the attention weight of the KTH dimension in region g, ϑ_g represents the standardized indicator vector of region g,k represents the rural revitalization evaluation dimension set, R_k is the dimension mapping matrix, and s_k is the attention parameter vector. Through this formula, the model can adaptively adjust the measure weights of each dimension according to the development foundation of different regions and the sinking type of enterprises.

The score of the comprehensive synergy effect is determined by the state of the regional indicators, the role of the sinking path of the enterprise and the regional carrying capacity, and its calculation formula is as follows:

$$C_g(l)=\sum_{k\in K}\pi_{g,k}\,\vartheta_{g,k}(l)+\varrho_g(l)\cdot\upsilon_g(l) \tag{13}$$

Here, $Cg(\ell)$ represents the synergy effect score of region g at time step ℓ, $\vartheta_{g,k}(\ell)$

represents the standardized index state at this time step, $\varrho_g(\ell)$ represents the effect strength of the sinking path of specialized and new enterprises on region g, and $\upsilon_g(\ell)$ represents the regional carrying capacity coefficient. The higher the score, the more fully the industrial synergy and development drive between enterprise subsidence and rural revitalization. The time series evolution prediction mechanism of the model is shown in Figure 3. The mechanism takes the sinking signal of enterprises, industrial correlation data, rural development indicators and policy environment information as the basic input, and forms a dynamic state sequence that can be used for prediction after sequence cleaning, time window division and time alignment. Then, the model extracts the evolution characteristics of rural revitalization in the dynamic time embedding, cross-modal fusion and state memory modules, and combines spatial-temporal dependency modeling, multi-step prediction and trend inference to generate future synergy effect scores, rural revitalization change trends and path adjustment suggestions. The feedback update link further modifies the historical state memory and prediction parameters, so that the model can continuously adapt to the changes of industrial relations and the fluctuations of regional development states in the process of enterprise chain sinking.

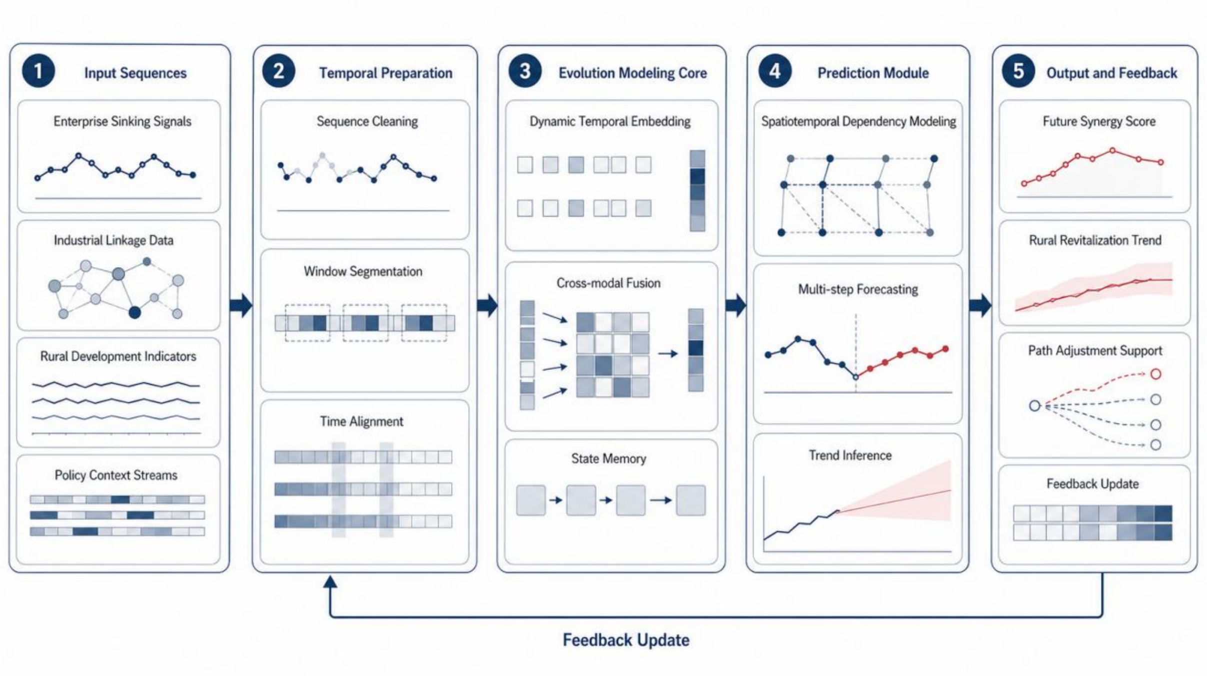

Figure 3: Diagram of time series evolution prediction mechanism

In order to further characterize the linkage propagation relationship between regions, this paper constructs the spatio-temporal dependence coefficient, and incorporates the spatial proximity, industrial association and synergistic effect differences into the unified calculation. The formula is as follows:

$$D_{g,b}(l)=\mathrm{Softmax}\left(\frac{\mathbf{z}_g(l)^{\mathrm{T}}\mathbf{H}_d\mathbf{z}_b(l)}{\sqrt{d_z}}+\kappa_{g,b}\right) \tag{14}$$

Here, $D_{g,b}(\ell)$ represents the strength of spatial-temporal dependence between region g and region b at time step ℓ; $z_g(\ell)$ and $z_b(\ell)$ represent the dynamic state vectors of the two regions, respectively; H_d represents the dependency mapping matrix; dz represents the dimension of the state vector; and $\kappa_{g,b}$ represents the inter-region industrial ties or spatial proximity prior.

This coefficient can reflect the diffusion and conduction of the sinking effect between different regions.

In the prediction stage, this paper adopts the combination of time series Transformer and gated update structure to learn the long-term dependence of rural revitalization status. Regional dynamic state update formula is as follows:

$$\mathbf{z}_g(\mathrm{l}+1)=\mathrm{GRU}\left(\mathbf{z}_g(\mathrm{l}),C_g(\mathrm{l}),\sum_{b\in N_g} D_{g,b}(\mathrm{l})\mathbf{z}_b(\mathrm{l})\right) \tag{15}$$

Here, $z_g(\ell+1)$ represents the predicted state vector of region g at the next time step, N_g represents the set of neighborhoods with industrial or spatial associations with region g, and $\mathrm{GRU}(\cdot)$ represents the gated recurrent unit. The formula inputs the region's own state, synergy effect score and neighborhood propagation state into the prediction module together, which can improve the model's ability to capture lagged effects and linkage changes.

In order to ensure the stability of measurement results and prediction results at the same time, a multi-task loss function is used in model training, and the synergy effect fitting error, future state prediction error and model complexity constraints are jointly incorporated into the optimization objective. The formula is:

$$\mathrm{L_{evo}}=\frac{1}{|G|}\sum_{g\in G}\left(\widehat{C}_g-C_g^*\right)^2+\frac{1}{|G|}\sum_{g\in G}\left\|\hat{\mathbf{z}}_g-\mathbf{z}_g^*\right\|_2^2+\lambda_{\mathrm{e}}\|\mathbf{\Psi}\|_2^2 \tag{16}$$

Here, $\mathrm{L_{evo}}$ represents the evolutionary prediction loss, $\widehat{C}_g$ represents the synergy score predicted by the model, C_g^* represents the true or calibrated synergy label, $\hat{z}_g$ represents the predicted state vector, z_g^* represents the actual state vector, λ_e represents the regularization weight, and Ψ represents the set of parameters of this prediction model. The loss function can simultaneously constrain the measure accuracy and prediction stability.

In general, the method in this section extends the rural revitalization synergy effect from static evaluation to dynamic evolution analysis through index normalization, attention weight allocation, synergy effect score calculation, spatio-temporal dependence modeling, and multi-task prediction optimization. The model can not only judge the current contribution of the subsidisation of specialized and special new enterprises to rural revitalization, but also predict the subsequent development trend, and provide computer-aided decision-making basis for the subsidisation path adjustment, resource allocation optimization and regional collaborative governance.

4 Experimental results and analysis

4.1 Experimental environment Configuration and multi-modal sample data set construction

In order to verify the effectiveness of the multimodal data-driven model in the identification of the chain sinking path of specialized and special enterprises and the prediction of the co-evolution of rural revitalization, this paper constructs a comprehensive experimental dataset oriented to enterprises, industrial chains and rural areas. The experimental data mainly come from the public information of enterprises, patent and intellectual property data, upstream and downstream cooperation records of the industrial chain, local policy texts, county industrial statistics, transportation location data and rural development indicator data. After data collection, the enterprise name, unified social credit code, regional code and industry classification are unified, duplicate records and abnormal samples are deleted, and the preprocessing is completed by using missing value imputation, interval normalization, text segmentation, semantic vector coding and space coordinate mapping. Finally, a multi-modal sample library containing enterprise capabilities, industrial collaboration, policy semantics, spatial location and rural acceptance conditions was formed.

The experimental running environment uses Windows Server 2019 operating system, the core computing module is implemented based on Python 3.10 and PyTorch 2.1, the text semantic encoding part uses Transformer structure, and the graph relationship learning part uses heterogeneous graph neural network. The time series prediction part adopts the prediction structure combining GRU and Temporal Transformer. The hardware configuration is Intel Xeon Silver 4214R processor, NVIDIA RTX 3090 GPU and 128 GB memory, which can meet the needs of multi-modal feature extraction, graph structure training and rolling prediction calculation. The dataset was divided into training set, validation set and test set according to 7：1.5：1.5. The training set was used for parameter learning, the validation set was used to adjust the fusion weights and model hyperparameters, and the test set was used to evaluate the effect of chain sinking path identification and co-evolution prediction. To ensure the stability of the experimental results, each group of experiments was repeated five times, and the average value was taken as the final result. The composition of multimodal sample data is shown in Table 2.

Table 2: Multi-modal sample data composition table

Data Category	Collected Content	Sample Size or Dimension	Preprocessing Method	Technical Function
Enterprise Structured Data	Registered capital, years since establishment, revenue range, number of patents, proportion of R&D personnel	12,846 enterprises, 42 fields	Deduplication cleaning, missing value imputation, interval normalization	Represents the innovation capacity and industrial driving foundation of specialized and sophisticated enterprises
Industrial Chain Collaboration Data	Upstream and downstream cooperation, procurement and sales relationships, joint R&D, project supporting records	145,670 relational edges	Enterprise entity alignment, relation type annotation, edge weight standardization	Constructs the industrial network relationship for enterprise chain sinking
Policy and Text Data	Industrial policies, investment promotion announcements, enterprise reports, project publicity texts	52,600 text segments	Word segmentation cleaning, stop-word filtering, Transformer semantic encoding	Extracts policy orientation, industrial matching, and regional support semantics
Spatial Location Data	Enterprise coordinates, industrial park locations, transportation distance, logistics accessibility time	3,218 regional nodes	Geocoding, coordinate correction, distance matrix calculation	Determines the spatial accessibility of enterprise sinking paths
Rural Development Data	Industrial foundation, employment structure, infrastructure, public services, characteristic resources	2,084 township units, 36 indicators	Indicator unification, outlier correction, comprehensive standardization	Measures rural undertaking capacity and revitalization status
Remote Sensing Auxiliary Data	Land use, road density, construction land changes, industrial spatial distribution	6,200 regional image patches	Size cropping, image enhancement, CNN feature extraction	Assists in identifying rural industrial space and resource utilization characteristics

It can be seen from Table 2 that the experimental data in this paper cover enterprise capability, industrial collaboration, policy semantics, spatial location, rural development and remote sensing auxiliary information, which can completely support chain sinking path identification and co-evolution prediction. The construction of the multi-modal sample library provides a unified data basis for subsequent algorithm comparison, feature ablation and stability verification.

4.2 Comparison and analysis of identification effect of chain sinking path under different algorithms

In order to verify the effectiveness of the model in the chain sinking path identification task of specialized and special new enterprises, Random Forest, XGBoost, GCN and GAT are selected as comparison algorithms, and experiments are carried out under the same training set, validation set and test set conditions. The evaluation metrics include Accuracy, Precision, Recall, F1-score, and AUC. The overall results show that traditional machine learning methods have certain adaptability to structural features, but their performance is limited when dealing with enterprise relationships, spatial dependencies and multi-modal semantic information. Although the graph neural network method can depict the industrial chain correlation, the fusion depth of heterogeneous modal information is still insufficient. Figure 4 shows the performance comparison of the chain sinking path recognition under different algorithms.

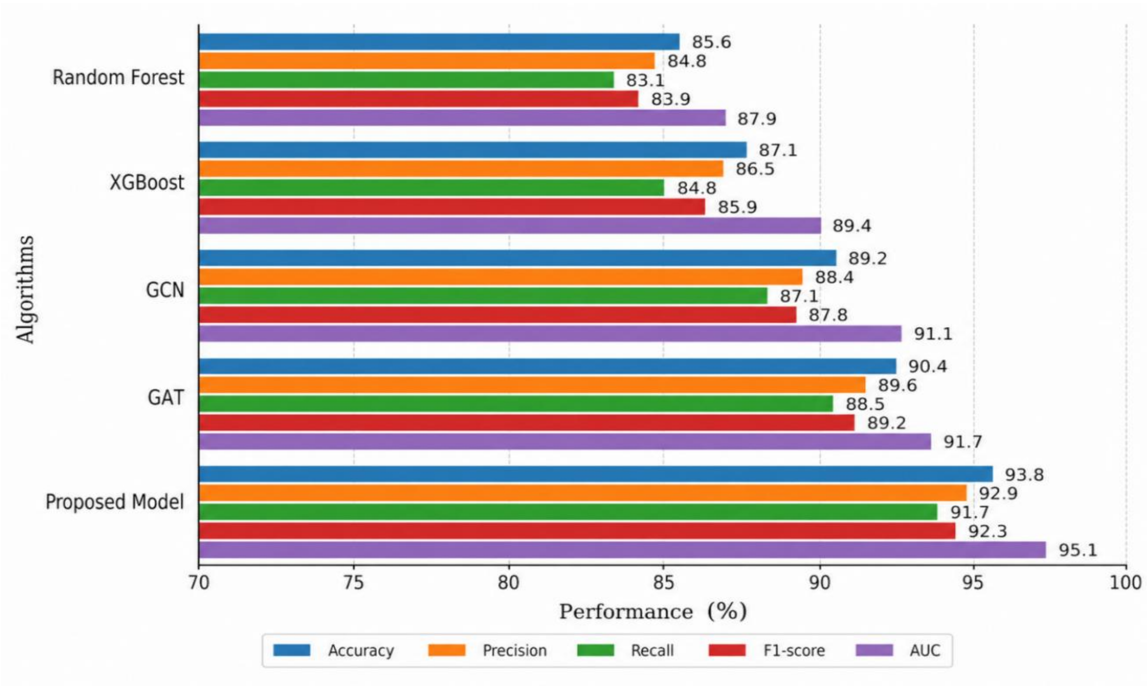

Figure 4: Bar charts comparing the performance of chain sinking path recognition under different algorithms

As shown in Figure 4, the proposed model performs best in all indicators, with Accuracy of 93.8%, Precision of 92.9%, Recall of 91.7%, F1-score of 92.3%, and AUC of 95.1%. Compared with GAT model, the Accuracy is increased by 3.4 percentage points, and the F1-score is increased by 3.1 percentage points. Compared with the GCN model, the AUC was increased by 4.0 percentage points. Compared with Random Forest and XGBoost, the proposed model improves the Recall index by 8.6 percentage points and 6.9 percentage points respectively. It can be seen that the method of fusing multimodal feature optimization and chain relationship modeling can more accurately identify the sinking path of enterprises, and maintain good recognition stability in complex industrial network scenarios.

4.3 Analysis of the influence of multi-modal feature fusion on the prediction performance of co-evolution

In order to investigate the contribution of different modal information to the prediction results of co-evolution, this paper sets up five groups of experiments under the same training conditions: "structured data only", "structured + text", "structured + text + space", "structured + text + space + supply chain" and "full modal integration", and focuses on comparing the changes of the model in indicators such as RMSE, MAE and R^2. The results show that although the single structured data can reflect the enterprise scale, innovation input and rural development foundation, the description of industrial synergy and policy semantics is still limited. With the gradual addition of text semantics, spatial location and supply chain correlation information, the model's ability to identify the impact path and regional evolution trend of chain subsidence continues to enhance. Taking the RMSE change as an example, Figure 5 shows the improvement of coevolution prediction error by different modal combinations.

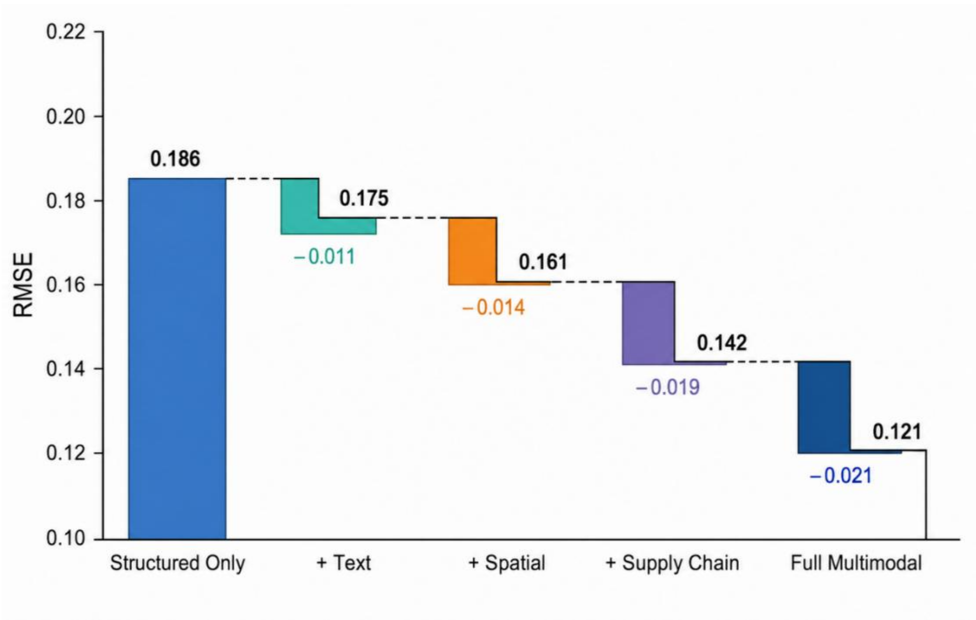

Figure 5: Waterfall plot of performance improvement of co-evolution prediction by different modal combinations

The waterfall chart shows that after the model is extended from "structured data only" to "full modal fusion", the RMSE decreases from 0.186 to 0.121, with a cumulative decrease of 34.9%. MAE decreased from 0.143 to 0.089, decreasing by 37.8%; R^2 increased from 0.781 to 0.914. The introduction of text modality mainly improves the expression of policy support and industry-oriented information, the spatial modality strengthens the linkage characteristics of regional acceptance conditions and location, and the supply chain modality further enhances the ability to describe the chain sinking relationship of enterprises.Figure 6 shows the strip plot of the confidence interval between the true value of the co-evolution prediction and the rolling prediction value.

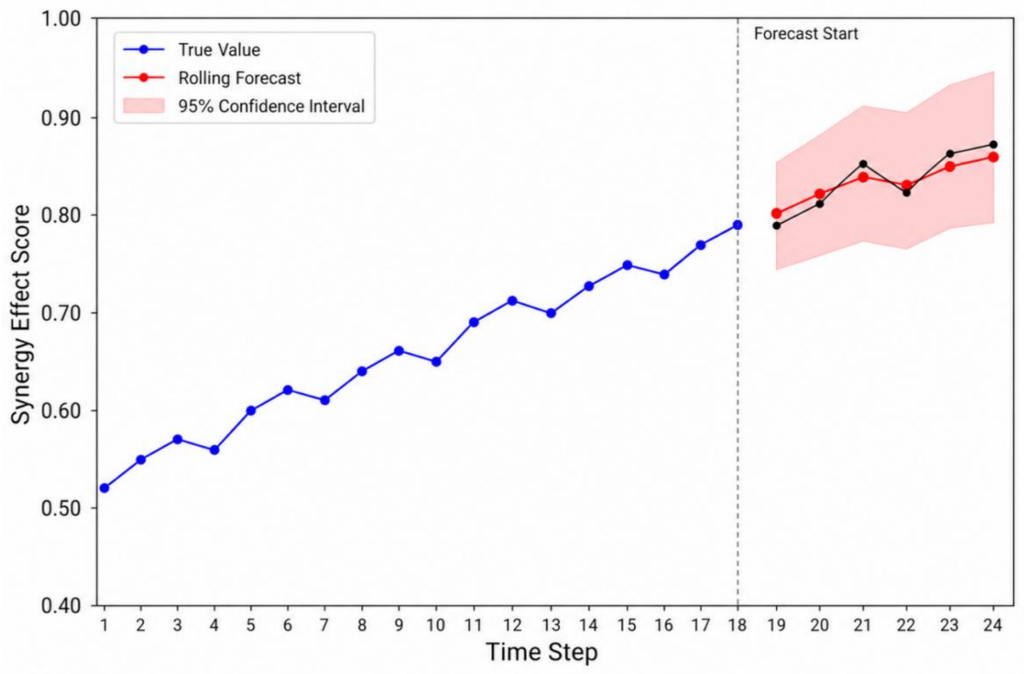

Figure 6: Strip chart of confidence intervals between true and rolling prediction values of co-evolution prediction

It can be seen that the model can better fit the real change trajectory of synergistic effects in the historical stage, and maintain a relatively stable trend extension ability in the future rolling prediction stage. The predicted mean value is basically near the real value, and the confidence interval bandwidth expands moderately with the increase of prediction step size, which conforms to the uncertainty propagation law of time series prediction. Within six rolling prediction time steps, the proportion of the true value falling into 95% confidence interval reaches 93.7%, and the mean absolute error is controlled within 0.031, which indicates that the constructed multi-modal fusion model not only has good prediction accuracy, but also has strong trend stability and interval estimation ability. In general, multi-modal feature fusion can significantly improve the prediction performance of co-evolution, and provide more reliable data support for subsequent enterprise sinking path optimization and rural revitalization dynamic decision-making.

4.4 Analysis on the driving effect of specialized and special new enterprises sinking on rural revitalization indicators

After completing path identification and co-evolution prediction, this paper further analyzes the driving effect of the chain sinking of specialized and special new enterprises on each dimension index of rural revitalization. Considering that enterprise subsidence is not a single economic input, but a continuous transmission of technology, orders, talents, brands and data capabilities to county and rural nodes, this paper selects five dimensions of industrial development, employment absorption, innovation diffusion, public services and resource utilization to compare the synergistic effects under different subsidence intensities and different subsidence paths. The results show that enterprise chain subsidence can significantly improve the comprehensive score of rural revitalization, but the response speed and improvement range of different dimensions are not consistent. Among them, industrial development and innovation diffusion are more sensitive to the intensity of enterprise subsidence, while employment absorption and public service improvement show a certain lag.

Figure 7 shows the relationship between enterprise subsidence intensity and rural revitalization dimension response.

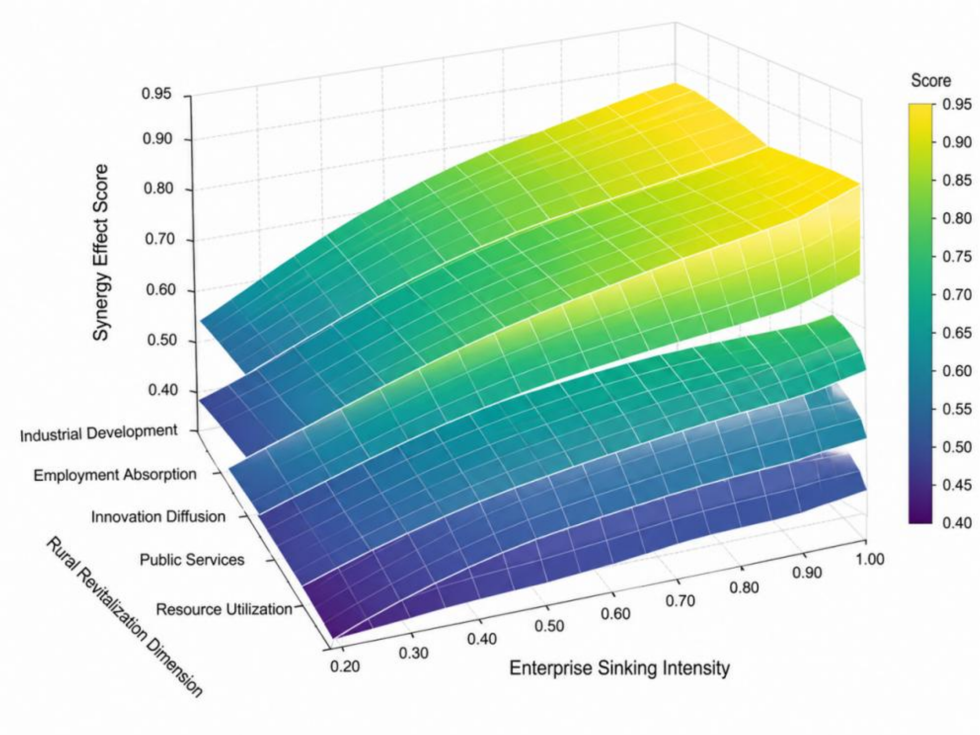

Figure 7:Three-dimensional surface diagram of the relationship between the sinking intensity of enterprises and the dimensional response of rural revitalization

Figure 7 shows that as the sinking intensity of enterprises increases from 0.20 to 1.00, the comprehensive synergy effect score of rural revitalization increases from 0.47 to 0.88, showing a continuous strengthening trend. From the sub-dimension results, the innovation diffusion dimension improved the most significantly, with the score increasing from 0.49 to 0.91. The industrial development dimension increased from 0.46 to 0.89; The resource utilization dimension was increased from 0.44 to 0.82; The dimensions of employment absorption and public service increased from 0.43 and 0.41 to 0.79 and 0.76, respectively. The surface change shows that when the subsidence intensity is above 0.55, the response speed of each dimension is significantly accelerated, indicating that after the enterprise subsidence reaches a certain scale, a stronger superposition effect will be formed through supply chain expansion, technology spilt and industrial agglomeration.

In this paper, the typical paths are divided into four categories: technology diffusion type, supply chain embedding type, resource transformation type and service leading type, and the ridge plot is used to compare the distribution difference of synergistic effects of each path in the sample area.Figure 8 shows the distribution of synergistic effects of different chain sinking paths.

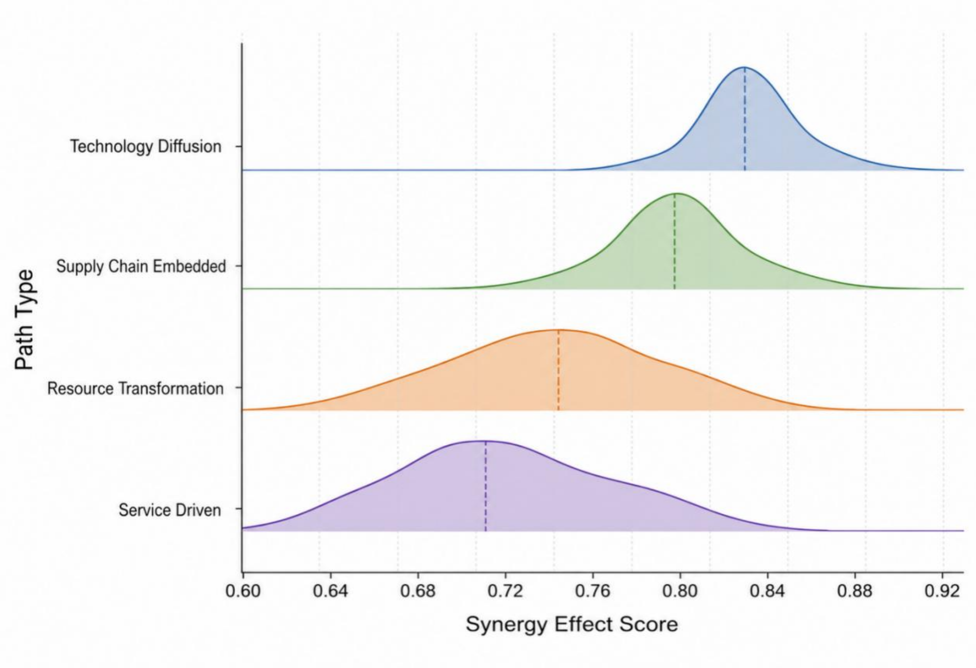

Figure 8 :Ridge diagram of synergistic effect distribution of different chain sinking paths

Figure 8 shows that the synergistic effect distribution of the technology diffusion path is the most right, with an average value of 0.84, and the high value interval is relatively concentrated, indicating that this path has the best performance in industrial upgrading and innovation driving. The mean value of the supply chain embedded path is 0.81, and the distribution is relatively stable, indicating that it has strong support for the promotion of county supporting capacity and employment promotion. The mean value of the resource transformation path is 0.76, and the distribution is wide, which reflects the influence of the difference of resource endowment in different regions on the effect release. The service-led path has a mean of 0.72, which, although the overall level is slightly lower, has complementary advantages in terms of public service improvement and consumption activation. On the whole, the proportion of high-value samples of the technology diffusion path and the supply chain embedding path reached 36.8% and 32.5%, respectively, which were significantly higher than those of the resource transformation path and the service leading path. Therefore, there are significant differences in the direction and intensity of the effect of different chain subsidence paths on rural revitalization, and the path with technology diffusion and supply chain embedding as the core is easier to form a sustained and stable synergistic gain.

4.5 Path optimization effect and stability verification of co-evolution model

The path optimization takes the score of the candidate sinking path, the suitability of the regional undertaking and the predicted value of the synergy effect as the joint goal, and screens the enterprise sinking schemes with high collaboration and high stability on the basis of ensuring that the prediction error is controllable. In order to verify the comprehensive performance of the proposed collaborative evolution model in path optimization and stability, this paper compares the proposed model with the basic model, the multimodal fusion module removal model, the time series prediction module removal model and the traditional weighted decision-making model, and evaluates it from three aspects: the comprehensive synergy effect score, the prediction error and the stability index. The path optimization effect and the distribution of the model stability Pareto front are shown in Figure 9.

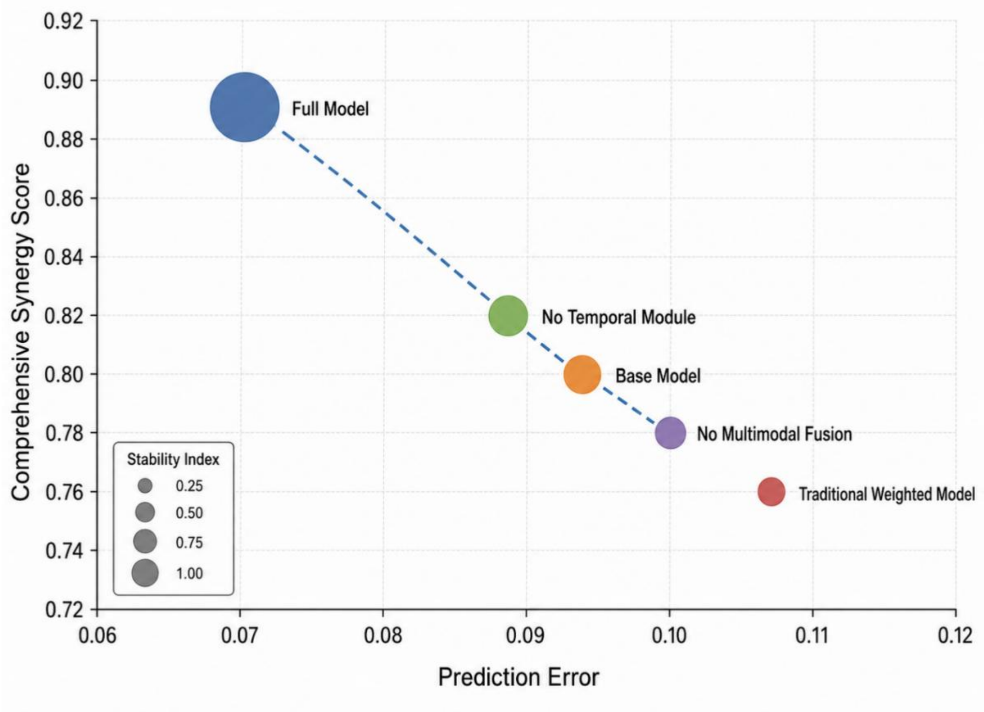

Figure 9: Bubble plot of Pareto front between path optimization effect and model stability

It can be seen that the bubbles corresponding to the proposed model are concentrated in the frontier optimal region, and a higher comprehensive synergy score is obtained under the condition of a lower prediction error, while maintaining a larger stability bubble scale. Specifically, the comprehensive synergy effect score of the proposed model reaches 0.89, the prediction error is reduced to 0.072, and the stability index is 0.93. Compared with the basic model, the comprehensive score is increased by 11.3%, and the error is decreased by 24.2%. Compared with the traditional weighted decision model, the stability index is increased by 13.4%. This shows that the constructed co-evolution model can not only provide a better path scheme for enterprise chain sinking, but also maintain good robustness and decision reliability under multiple scene disturbances.

5 Conclusion

Focusing on the co-evolution problem of the chain sinking of specialized and special enterprises and rural revitalization, this paper constructs a computational model that integrates multi-modal feature optimization, heterogeneous graph relational learning and time series prediction. The study shows that the joint modeling of structured firm data, policy text, spatial location, supply chain collaboration and rural development indicators can more completely depict firm capabilities, industrial connectivity and regional acceptance conditions. The experimental results verify the effectiveness of the model. The Accuracy, Precision, Recall, F1-score and AUC of the proposed model reach 93.8%, 92.9%, 91.7%, 92.3% and 95.1%, respectively. It is superior to comparison algorithms such as Random Forest, XGBoost, GCN and GAT. The multi-modal fusion further improves the prediction performance of co-evolution, the RMSE is decreased by 34.9%, the MAE is decreased by 37.8%, and the R^2

is increased to 0.914. The driving effect analysis showed that when the enterprise sinking intensity increased from 0.20 to 1.00, the comprehensive synergy effect score of rural revitalization increased from 0.47 to 0.88, and the technology diffusion and supply chain embedding paths were more stable. In the path optimization verification, the comprehensive score of the model reaches 0.89 and the stability index reaches 0.93. In the future, real-time industrial monitoring data and cross-regional transfer learning mechanism can be further introduced to enhance the generalization ability of the model in different regions and complex industrial scenarios.

Funding

This work was supported by 2026 Ji'an Social Science Planning Project (No. 26GHA108); Doctoral Research Startup Project (Social Sciences) of Jinggangshan University (BSQD202501).

About the Author

Liping Yang is affiliated with the School of Business, Jinggangshan University, Ji’an, China, and serves as the corresponding author of this study. Her research interests include corporate governance, the digital economy, and supply chain management. She can be contacted at yangliping@jgsu.edu.cn

Jie Shen is affiliated with the School of Finance and Accounting, Jiangxi Polytechnic University, Jiujiang, China. His research focuses on corporate finance, financial regulation, and firm innovation. He can be contacted at amcici233@163.com

Jiangnan Chen is affiliated with the Information Engineering School, Jiangxi Polytechnic University, Jiujiang, China. His research interests include information systems, digital technology, and data analytics. He can be contacted at xia_nan@jxpu.edu.cn

Jian Xiong is affiliated with the Information Engineering School, Jiangxi Polytechnic University, Jiujiang, China. His research focuses on information engineering, digital applications, and intelligent systems. He can be contacted at 21021@jxpu.edu.cn

References

[1] Matarazzo M, Penco L, Profumo G, Quaglia R. Digital transformation and customer value creation in Made in Italy SMEs: A dynamic capabilities perspective[J]. Journal of Business Research, 2021, 123: 642-656. DOI: 10.1016/j.jbusres.2020.10.033.

[2] Burström T, Parida V, Lahti T, Wincent J. AI-enabled business-model innovation and transformation in industrial ecosystems: A framework, model and outline for further research[J]. Journal of Business Research, 2021, 127: 85-95. DOI: 10.1016/j.jbusres.2021.01.016.

[3] Khurana I, Dutta D K, Ghura A S. SMEs and digital transformation during a crisis: The emergence of resilience as a second-order dynamic capability in an entrepreneurial ecosystem[J]. Journal of Business Research, 2022, 150: 623-641. DOI: 10.1016/j.jbusres.2022.06.048.

[4] Troise C, Corvello V, Ghobadian A, O’Regan N. How can SMEs successfully navigate

VUCA environment: The role of agility in the digital transformation era[J]. Technological Forecasting and Social Change, 2022, 174: 121227. DOI: 10.1016/j.techfore.2021.121227.

[5] Radicic D, Petković S. Impact of digitalization on technological innovations in small and medium-sized enterprises SMEs[J]. Technological Forecasting and Social Change, 2023, 191: 122474, 1-16. DOI: 10.1016/j.techfore.2023.122474.

[6] Škare M, de Obesso M M, Ribeiro-Navarrete S. Digital transformation and European small and medium enterprises SMEs: A comparative study using digital economy and society index data[J]. International Journal of Information Management, 2023, 68: 102594. DOI: 10.1016/j.ijinfomgt.2022.102594.

[7] Rajala A, Hautala-Kankaanpää T. Exploring the effects of SMEs' platform-based digital connectivity on firm performance: The moderating role of environmental turbulence[J]. Journal of Business & Industrial Marketing, 2023, 38(13): 15-30. DOI: 10.1108/JBIM-01-2022-0024.

[8] Plekhanov D, Franke H, Netland T H. Digital transformation: A review and research agenda[J]. European Management Journal, 2023, 41(6): 821-844. DOI: 10.1016/j.emj.2022.09.007.

[9] Clemente-Almendros J A, Nicoara-Popescu D, Pastor-Sanz I. Digital transformation in SMEs: Understanding its determinants and size heterogeneity[J]. Technology in Society, 2024, 77: 102483. DOI: 10.1016/j.techsoc.2024.102483.

[10] Romero I, Mammadov H. Digital transformation of small and medium-sized enterprises as an innovation process: A holistic study of its determinants[J]. Journal of the Knowledge Economy, 2025, 16(2): 8496-8523. DOI: 10.1007/s13132-024-02217-z.

[11] Merín-Rodrigáñez J, Dasí À, Alegre J. Digital transformation and firm performance in innovative SMEs: The mediating role of business model innovation[J]. Technovation, 2024, 134: 103027, 1-12. DOI: 10.1016/j.technovation.2024.103027.

[12] Merín-Rodrigáñez J, Dasí À, Alegre J, Hughes M. Dynamic managerial capabilities for digital transformation in innovative SMEs: What are the effects on new product development performance?[J]. Journal of Business Research, 2025, 201: 115709. DOI: 10.1016/j.jbusres.2025.115709.

[13] Kraus S, Durst S, Ferreira J J, Veiga P, Kailer N, Weinmann A. Digital transformation in business and management research: An overview of the current status quo[J]. International Journal of Information Management, 2022, 63: 102466. DOI: 10.1016/j.ijinfomgt.2021.102466.

[14] Elia G, Solazzo G, Lerro A, Pigni F, Tucci C L. The digital transformation canvas: A conceptual framework for leading the digital transformation process[J]. Business Horizons, 2024, 67(4): 381-398. DOI: 10.1016/j.bushor.2024.03.007.

[15] Heubeck T. Managerial capabilities as facilitators of digital transformation? Dynamic managerial capabilities as antecedents to digital business model transformation and firm performance[J]. Digital Business, 2023, 3(1): 100053. DOI: 10.1016/j.digbus.2023.

100053.

[16] Hassan S S, Meisner K, Krause K, Bzhalava L, Moog P. Is digitalization a source of innovation? Exploring the role of digital diffusion in SME innovation performance[J]. Small Business Economics, 2024, 62(4): 1469-1491. DOI: 10.1007/s11187-023-00826-7.

[17] Pfister P, Lehmann C. Measuring the success of digital transformation in German SMEs[J]. Journal of Small Business Strategy, 2023, 33(1): 1-19. DOI: 10.53703/001c.39679.

[18] Szukits Á, Móricz P. Towards data-driven decision making: The role of analytical culture and centralization efforts[J]. Review of Managerial Science, 2024, 18(10): 2849-2887. DOI: 10.1007/s11846-023-00694-1.

[19] Nucci F, Puccioni C, Ricchi O. Digital technologies and productivity: A firm-level investigation[J]. Economic Modelling, 2023, 128: 106524. DOI: 10.1016/j.econmod.2023.106524.

[20] Nell P C, Foss N J, Klein P G, Schmitt J. Avoiding digitalization traps: Tools for top managers[J]. Business Horizons, 2021, 64(2): 163-169. DOI: 10.1016/j.bushor.2020.11.005.

[21] Wurth B, Stam E, Spigel B. Toward an entrepreneurial ecosystem research program[J]. Entrepreneurship Theory and Practice, 2022, 46(3): 729-778. DOI: 10.1177/1042258721998948.

[22] Kennedy E D. Creating community: The process of entrepreneurial community building for civic wealth creation[J]. Entrepreneurship & Regional Development, 2021, 33(9-10): 816-836. DOI: 10.1080/08985626.2021.1964612.

[23] Bürgin R, Mayer H, Kashev A, Haug S. Digital multilocality: New modes of working between center and periphery in Switzerland[J]. Journal of Rural Studies, 2021, 88: 83-96. DOI: 10.1016/j.jrurstud.2021.09.024.

[24] Gerli P, Whalley J. Fibre to the countryside: A comparison of public and community initiatives tackling the rural digital divide in the UK[J]. Telecommunications Policy, 2021, 45(10): 102222. DOI: 10.1016/j.telpol.2021.102222.

[25] Lindberg J, Lundgren A S. The affective atmosphere of rural life and digital healthcare: Understanding older persons' engagement in eHealth services[J]. Journal of Rural Studies, 2022, 95: 77-85. DOI: 10.1016/j.jrurstud.2022.08.001.

[26] Rijswijk K, Klerkx L, Bacco M, Bartolini F, Bulten E, Scotti I, Dessein J, Brunori G. Digital transformation of agriculture and rural areas: A socio-cyber-physical system framework to support responsibilisation[J]. Journal of Rural Studies, 2021, 85: 79-90. DOI: 10.1016/j.jrurstud.2021.05.003.

[27] Gaw N, Yousefi S, Reisi Gahrooei M. Multimodal data fusion for systems improvement: A review[J]. IISE Transactions, 2022, 54(11): 1098-1116. DOI: 10.1080/24725854.2021.1987593.

[28] Sarafan M, Lawson B, Roehrich J K, Squire B. Knowledge sharing in project-based supply networks[J]. International Journal of Operations & Production Management, 2022, 42(6): 852-874. DOI: 10.1108/IJOPM-06-2021-0394.