Research on the Transformation of Regional Economic Green Development Model Driven by Technological Innovation

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Abstract. This paper, addressing the needs of high-quality regional economic development and green and low-carbon governance, constructs a computational analysis framework for the synergistic effects of technological innovation, industrial structure, energy efficiency, carbon emission constraints, and economic quality. It also proposes a graph attention algorithm, TIGT-GA, for driving green transformation through technological innovation. This algorithm treats regions as graph nodes and constructs technological cooperation, industrial linkages, energy structure similarities, and policy synergies as graph edges. It introduces green constraint factors and a gated temporal state update mechanism into the traditional graph attention mechanism, thereby achieving prediction of regional green transformation index, level identification, and policy scenario simulation. Experiments are conducted using panel structure data from 2013 to 2023 for 30 regions, and comparisons are made with algorithms such as entropy-weighted TOPSIS, SVR, random forest, XGBoost, BP neural network, LSTM, and ordinary GAT. The results show that TIGT-GA has an RMSE of 0.041, an MAE of 0.028, an R^2 of 0.934, and a rating accuracy of 91.6%, which is 28.07% lower than the RMSE of ordinary GAT and 33.87% lower than XGBoost. Policy simulation results show that when R&D intensity increases by 20%, the regional average green transition index increases from 0.612 to 0.684, an increase of 11.76%; when R&D investment, digital infrastructure, and green finance support are synergistically improved, the green transition index reaches 0.712, and the carbon emission intensity per unit of GDP decreases by 10.27%. The research indicates that technological innovation can significantly promote regional green transformation, but its effect needs to be released through the synergy of technology diffusion, digital infrastructure, industrial upgrading, and green policies.

Keywords: Technological innovation, regional economy, green development, graph attention network, algorithm comparison, policy simulation.

1. Introduction

Regional economic development has long been influenced by resource constraints, environmental carrying capacity, and industrial restructuring. For a long period in the past, some regions relied on energy consumption, capital investment, and land expansion to achieve economic growth. However, this growth model easily leads to low resource utilization efficiency, high pollution emissions, and insufficient motivation for industrial upgrading. With the increasing demands for green and low-carbon development, regional economic development models need to shift from scale expansion to innovation-driven, efficiency-enhancing, and green collaboration. Technological innovation can improve resource allocation efficiency through green technology R&D, digital governance, energy-saving process transformation, and industrial chain optimization, and is a key driving force for promoting regional green development. In the past five years, digital economy, green technology innovation, green total factor productivity, and carbon emission reduction efficiency have become research hotspots. Existing research shows that digital economy can improve resource allocation efficiency and green development efficiency, green technology innovation can promote industrial structure upgrading, and environmental regulations can force enterprises to carry out green innovation [1-4]. However, existing research still has three shortcomings. First, many studies use static comprehensive evaluation or traditional econometric models, which are difficult to characterize technology diffusion and industrial linkages between regions. Second, although some machine learning models can improve prediction accuracy, they lack explicit expression of carbon emission constraints and green development goals. Third, existing research rarely conducts simultaneous algorithm prediction, algorithm comparison, ablation experiments, and policy scenario simulations, resulting in insufficient model interpretability and policy application value [5-6]. This paper first constructs a multi-source feature system for regional technological innovation and green development, incorporating variables such as R&D investment, patent output, digital infrastructure, technology transfer, energy efficiency, carbon emission intensity, and industrial structure upgrading into the model input. Second, it proposes the TIGT-GA green transformation graph attention algorithm, introducing a green constraint attention mechanism and a gated time-series update mechanism to enhance the model's ability to express the dynamic evolution of green transformation and regional correlations. Finally, it designs multi-algorithm comparison experiments, time-series prediction experiments, policy scenario simulation experiments, and ablation experiments to verify the algorithm's performance from the perspectives of prediction accuracy, convergence stability, policy sensitivity, and module effectiveness.

2. TIGT-GA Green Transformation Graph Attention Algorithm Design

2.1. Overall Algorithm Idea

The basic idea of the TIGT-GA algorithm is to transform the regional green transformation problem into a graph structure learning problem. Let the set of regions be $V = \{v_1, v_2, \cdots, v_N\}$, with each region corresponding to a graph node; the relationships between regions in terms of technological cooperation, industrial structure similarity, energy structure similarity, and policy synergy correspond to graph edges [7]. The model learns the influence strength between regions through a graph attention mechanism, and incorporates a green constraint term into the attention weights, enabling the model to identify the positive diffusion effects of regions with strong low-carbon, high-efficiency, and innovative capabilities. Figure 1 shows the algorithm flow.

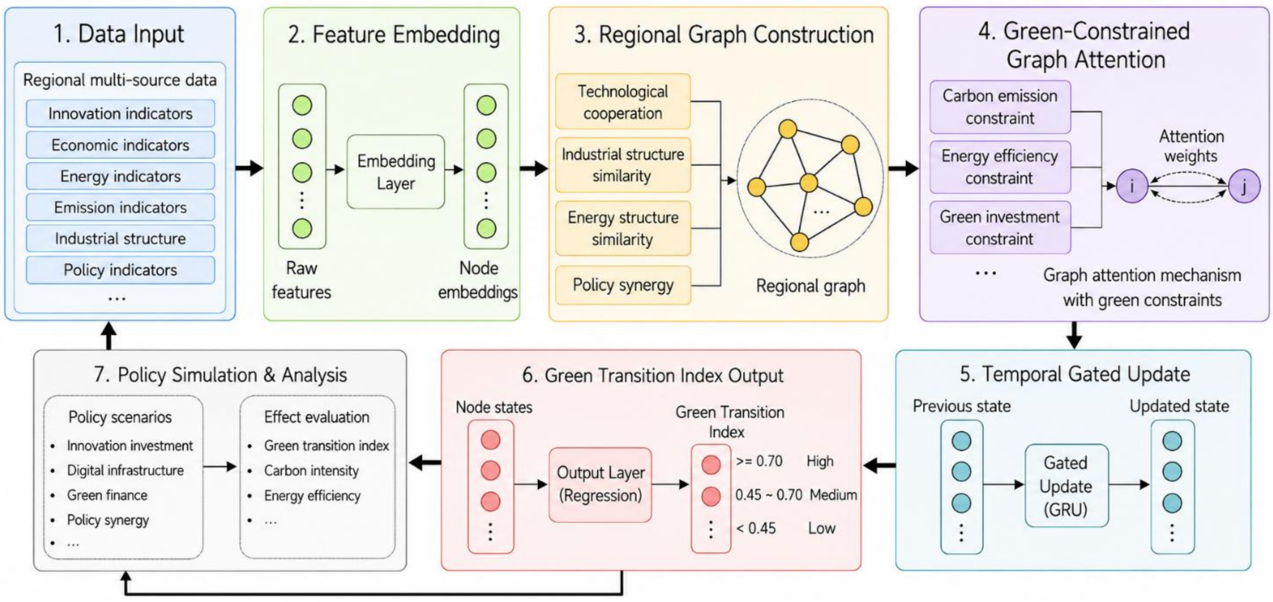

Figure 1. Algorithm Flow.

2.2. Multi-Source Feature Embedding for Regions

Let the original feature vector of the i region in year $t$be:

$$\mathbf{x}_{i,t} = [R_{i,t}, P_{i,t}, D_{i,t}, T_{i,t}, E_{i,t}, C_{i,t}, S_{i,t}, G_{i,t}] \quad (1)$$

Where $R_{i,t}$ represents R&D intensity, $P_{i,t}$ represents the number of patents granted, $D_{i,t}$ represents the level of digital infrastructure, $T_{i,t}$ represents the technology transfer rate,

$E_{i,t}$ represents energy efficiency, $C_{i,t}$ represents carbon emission intensity, $S_{i,t}$ represents the industrial structure upgrading index, and $G_{i,t}$ represents the proportion of green investment. Due to the different dimensions of the various indicators, this paper uses range standardization to process the original data.

$$\bar{x}_{i,t}^{k} = \frac{x_{i,t}^{k} - \min(x^k)}{\max(x^k) - \min(x^k) + \varepsilon} \tag{2}$$

Where $x_{i,t}^{k}$ represents the original value of the k index, and ε is a small constant to avoid the denominator being zero. The normalized features are input into the nonlinear mapping layer to obtain the initial region embedding:

$$\mathbf{h}_{i,t}^{(0)} = \sigma\left(\mathbf{W}_x \bar{\mathbf{x}}_{i,t} + \mathbf{b}_x\right) \tag{3}$$

Where $\mathbf{W}_x$ is the feature mapping matrix, $\mathbf{b}_x$ is the bias term, and $\sigma(\cdot)$ is the ReLU activation function.

2.3. Construction of Regional Green Correlation Graph

The strength of green correlation between regions is jointly determined by technological cooperation, similarity of industrial structure, differences in energy efficiency, and differences in carbon emissions. The comprehensive edge weight is defined as:

$$A_{ij,t} = \lambda_1 \frac{\mathbf{p}_{i,t}^{T} \mathbf{p}_{j,t}}{\|\mathbf{p}_{i,t}\| \|\mathbf{p}_{j,t}\|} + \lambda_2 e^{-\frac{|E_{i,t} - E_{j,t}|}{\tau_E}} + \lambda_3 e^{-\frac{|C_{i,t} - C_{j,t}|}{\tau_C}} + \lambda_4 \frac{Coop_{ij,t}}{\max(Coop_t)} \tag{4}$$

Where $\mathbf{p}_{i,t}$ and $\mathbf{p}_{j,t}$ represent the regional industrial structure vectors, $Coop_{ij,t}$ represents the intensity of inter-regional technological cooperation, τ_E and τ_C are smoothing coefficients, and $\lambda_1, \lambda_2, \lambda_3, \lambda_4$ are weighting coefficients. To reduce the impact of weakly correlated noise, a threshold function is introduced:

$$\tilde{A}_{ij,t} = \begin{cases} A_{ij,t}, & A_{ij,t} \geq \theta \\ 0, & A_{ij,t} < \theta \end{cases} \tag{5}$$

This graph structure reflects the spatial spillover relationships of regional green transformation. If two regions have similar industrial structures, close technological cooperation, and small differences in energy efficiency, they have a strong correlation in green transformation; conversely, lower edge weights have less impact on attention propagation.

2.4. Green Constraint Multi-Head Attention Mechanism

Ordinary graph attention networks typically calculate attention weights based solely on node feature similarity, failing to distinguish between high-carbon growth and green growth [8]. This paper introduces a green constraint vector, incorporating carbon emissions, energy efficiency, green investment, and differences in industrial structure into the attention calculation:

$$\mathbf{q}_{ij,t} = \left[\Delta C_{ij,t}, \Delta E_{ij,t}, \Delta G_{ij,t}, \Delta S_{ij,t}\right] \tag{6}$$

$$\Delta C_{ij,t} = \left|C_{i,t} - C_{j,t}\right|, \quad \Delta E_{ij,t} = \left|E_{i,t} - E_{j,t}\right|, \quad \Delta G_{ij,t} = \left|G_{i,t} - G_{j,t}\right|, \quad \Delta S_{ij,t} = \left|S_{i,t} - S_{j,t}\right| \tag{7}$$

The region relevance score of the m attention head is:

$$e_{ij,t}^{m} = LeakyReLU\left((\mathbf{a}^m)^T \left[\mathbf{W}^m \mathbf{h}_{i,t}^{(l)} \| \mathbf{W}^m \mathbf{h}_{j,t}^{(l)} \| \tilde{A}_{ij,t} \| \mathbf{q}_{ij,t}\right]\right) \tag{8}$$

The green penalty item is defined as:

$$\Omega_{ij,t} = \eta_1 \Delta C_{ij,t} - \eta_2 \Delta E_{ij,t} - \eta_3 \Delta G_{ij,t} - \eta_4 \Delta S_{ij,t} \tag{9}$$

The green constraint attention weights are:

$$\alpha_{ij,t}^{m}=\frac{\exp\left(e_{ij,t}^{m}-\Omega_{ij,t}\right)}{\sum_{k\in\mathcal{N}_i}\exp\left(e_{ik,t}^{m}-\Omega_{ik,t}\right)} \tag{10}$$

Node features updated as follows:

$$\mathbf{h}_{i,t}^{(l+1)}=\|_{m=1}^{M}\sigma\left(\sum_{j\in\mathcal{N}_i}\alpha_{ij,t}^{m}\,\mathbf{W}^{m}\mathbf{h}_{j,t}^{(l)}\right) \tag{11}$$

Where M represents the number of attention heads, and $\|$ represents the splicing operation. The multi-head mechanism can capture information on technology diffusion, industrial collaboration, and green constraints from different subspaces.

2.5. Time-Series Transformation State Update

Regional green transformation exhibits significant time accumulation; technological investment and green technology applications often do not immediately translate into green development performance. To characterize this lag effect, this paper introduces a gated time-series state update mechanism:

$$\boldsymbol{z}_{i,t}=\sigma\left(\boldsymbol{W}_z\boldsymbol{h}_{i,t}+\boldsymbol{U}_z\boldsymbol{s}_{i,t-1}+\boldsymbol{b}_z\right) \tag{12}$$

$$\mathbf{r}_{i,t}=\sigma\left(\mathbf{W}_r\mathbf{h}_{i,t}+\mathbf{U}_r\mathbf{s}_{i,t-1}+\mathbf{b}_r\right) \tag{13}$$

$$\tilde{\mathbf{s}}_{i,t}=\tanh\left(\mathbf{W}_s\mathbf{h}_{i,t}+\mathbf{U}_s\left(\mathbf{r}_{i,t}\odot\mathbf{s}_{i,t-1}\right)+\mathbf{b}_s\right) \tag{14}$$

$$\mathbf{s}_{i,t}=\left(1-\mathbf{z}_{i,t}\right)\odot\mathbf{s}_{i,t-1}+\mathbf{z}_{i,t}\odot\tilde{\mathbf{s}}_{i,t} \tag{15}$$

Where $\mathbf{z}_{i,t}$ is the update gate, $\mathbf{r}_{i,t}$ is the reset gate, $\mathbf{s}_{i,t}$ represents the hidden state of green transformation in the region in year t, and $\odot$ represents element-wise multiplication.

2.6. Green Transformation Index Prediction and Loss Function

The predicted value of the regional green transformation index is defined as:

$$\widehat{GTI}_{i,t}=\sigma\left(\mathbf{w}_o^{T}\mathbf{s}_{i,t}+b_o\right) \tag{16}$$

To improve model prediction accuracy and avoid high-carbon path bias, this paper designs a comprehensive loss function:

$$\mathcal{L}=\frac{1}{NT}\sum_{i=1}^{N}\sum_{t=1}^{T}\left(\widehat{GTI}_{i,t}-GTI_{i,t}\right)^2+\mu_1\sum_{i,t}\max\left(0,\hat{C}_{i,t}-C_{i,t}^{max}\right)+\mu_2\parallel\Theta\parallel_2^2 \tag{17}$$

The first term represents the prediction error of the green transition index, the second is the carbon emission constraint penalty term, and the third is the parameter regularization term. Through this loss function, the model fits the green transition index while penalizing carbon emission over-constraint scenarios.

3. Experimental Simulation Design

3.1. Data Source and Sample Construction

The experiment uses panel data from 2013 to 2023 for 30 regions, resulting in 330 annual regional samples. Since this paper focuses on verifying the algorithm mechanism and policy simulation capabilities, the experimental data is generated using publicly available statistical indicators [9]. The range and trends of variables refer to the general patterns of regional innovation input, energy consumption, carbon emission intensity, and industrial structure changes. Variables include R&D intensity, number of patent authorizations, digital infrastructure level, technology transfer rate, energy consumption per unit of GDP, carbon emission intensity, green investment ratio, and industrial structure upgrading index. Missing values are filled using the mean of adjacent years, outliers are corrected using the 3σ principle, and all variables are standardized to 0-1. The ratio of training set, validation set, and test set is set to 7:1:2.

3.2. Experimental Environment and Parameter Settings

The experimental platform was Python 3.10, and the deep learning framework was PyTorch. The TIGT-GA model had a hidden layer dimension of 64, 4 attention heads, a learning rate of 0.001, 300 training epochs, Adam as the optimizer, Dropout set to 0.20, and a batch size of 32. The region association graph threshold θ was set to 0.30, and the green penalty parameters $\eta_1, \eta_2, \eta_3, \eta_4$ were set to 0.40, 0.20, 0.20, and 0.20, respectively. To ensure fair algorithm comparison, all deep learning models used the same training and test sets, and the optimal parameters were selected on the validation set.

3.3. Comparison Algorithm Settings

To avoid overly simplistic experimental results, seven comparison algorithms were set up. Entropy-weighted TOPSIS represents the traditional static comprehensive evaluation method; SVR represents the small-sample nonlinear regression method; Random Forest and XGBoost represent ensemble learning methods; BP neural network represents the basic deep learning method; LSTM represents the temporal deep learning method; and ordinary GAT represents the graph neural network method without green constraints and gated temporal mechanisms [10]. By comparing these algorithms with TIGT-GA, the effectiveness of the proposed algorithm can be verified from four levels: static evaluation, machine learning, temporal learning, and graph structure learning.

3.4. Evaluation Metrics

To comprehensively evaluate model performance, this paper uses Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), Coefficient of Determination (R^2), Class Recognition Accuracy, and Training Time as evaluation metrics. RMSE and MAE measure the prediction error of the green transition index, MAPE reflects the relative prediction error, R^2 measures the model's fit, Class Recognition Accuracy evaluates the model's classification performance for low-, medium-, and high-transition regions, and Training Time analyzes the algorithm's computational efficiency.

4. Experimental Results and Analysis

4.1. Comparison of Prediction Performance of Multiple Algorithms

Table 1 shows the comparison results of different algorithms in the green transition index prediction task. It can be seen that TIGT-GA performs best in all prediction metrics, with an RMSE of 0.041, MAE of 0.028, MAPE of 4.62%, R^2 reaching 0.934, and a Class Recognition Accuracy of 91.6%. Compared to the standard GAT, TIGT-GA reduced the RMSE from 0.057 to 0.041, a decrease of 28.07%, indicating that the green-constrained attention mechanism and the gated temporal update mechanism can significantly improve the predictive ability of the graph model [11]. Compared to XGBoost, TIGT-GA reduced the RMSE by 33.87%, indicating that in scenarios with regional diffusion relationships and temporal cumulative effects, simple ensemble learning models are insufficient to fully exploit the inter-regional correlation information.

Table 1. Performance comparison of different algorithms.

Algorithm	RMSE	MAE	MAPE (%)	R^2	Accuracy (%)	Training time (s)
Entropy TOPSIS	0.096	0.071	11.84	0.781	76.4	1.2
SVR	0.078	0.056	9.41	0.835	81.9	8.6
Random Forest	0.068	0.049	8.17	0.864	84.8	11.3
XGBoost	0.062	0.044	7.26	0.882	86.2	14.8
BP Neural Network	0.073	0.052	8.74	0.842	82.7	19.5
LSTM	0.064	0.046	7.58	0.874	85.9	27.6
GAT	0.057	0.039	6.51	0.891	86.7	31.2
TIGT-GA	0.041	0.028	4.62	0.934	91.6	38.7

Figure 1 shows the R^2 and rank recognition accuracy of different algorithms. TIGT-GA achieves an R^2 of 0.934 and an accuracy of 91.6%, indicating that it can not only reduce the prediction error of continuous exponential curves but also improve the ability to identify the rank of green transformation in regions. This result shows that when the boundaries of low-transformation, medium-transformation, and high-transformation regions are relatively close, the green constraint attention mechanism can enhance the model's ability to identify key differential variables.

4.2. Algorithm Convergence Comparison Analysis

To further verify the model training stability, this paper compares the changes in the validation set RMSE of BP neural network, LSTM, ordinary GAT, and TIGT-GA during 300 rounds of training [12]. The results are shown in Figure 2. BP neural network shows a rapid decrease in the first 100 rounds, but a higher convergence value in the later stages, indicating that it is insufficient in expressing complex regional relationships. LSTM can utilize historical information and its convergence result is better than that of BP neural network, but it still lacks inter-regional technology diffusion modeling. Ordinary GAT performs stably in the mid-to-late stages, but due to the lack of green constraints, the attention allocation to high-carbon growth regions and green growth regions is insufficient. TIGT-GA stabilizes after about 180 rounds, and the final validation set RMSE converges to around 0.041, demonstrating lower error and a more stable convergence process.

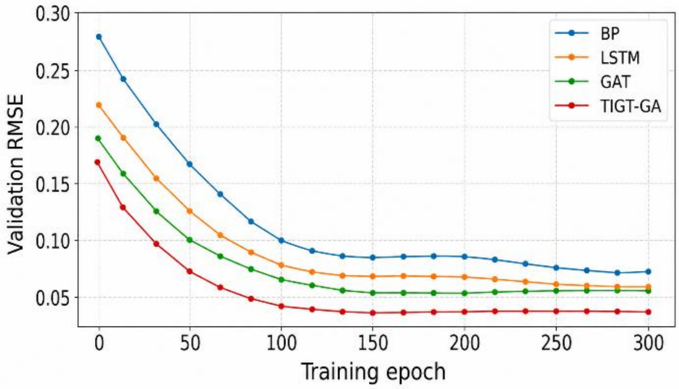

Figure 2. Convergence comparison of neural algorithms.

4.3. Time Series Forecast Results of Green Transition Index

Figure 3 shows the actual value, TIGT-GA predicted value, and ordinary GAT predicted value of the regional average green transition index from 2013 to 2023. The actual green transition index increased from 0.418 in 2013 to 0.672 in 2023, an overall increase of 60.77%. The TIGT-GA predicted curve is very close to the actual curve, and can capture the changes in green transition acceleration after 2017 and the stabilization of growth rate after 2021. Although ordinary GAT can reflect the overall upward trend, there are relatively significant deviations in 2016, 2019, and 2020, indicating that relying solely on graph structure propagation is still insufficient to fully identify green constraints and time lag effects.

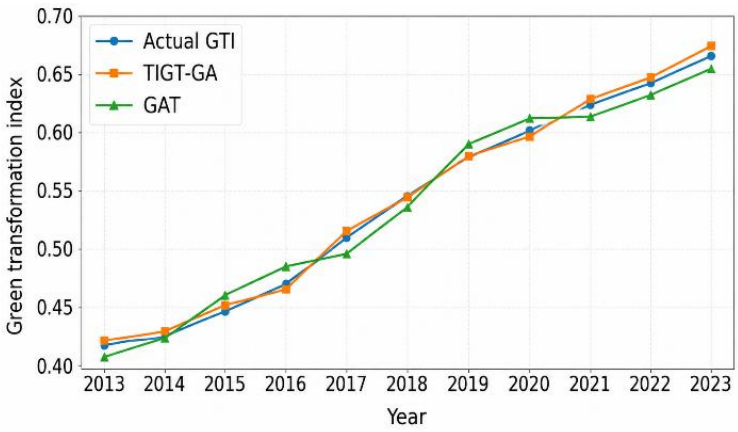

Figure 3. Actual and predicted green transformation index from 2013 to 2023.

4.4. Policy Scenario Simulation Results

To analyze the impact of changes in technological innovation investment on green transformation, this paper sets up five policy scenarios: a baseline scenario, a 10% increase in R&D investment, a 20% increase in R&D investment, a 30% increase in R&D investment, and a synergistic improvement scenario. The synergistic improvement scenario represents a simultaneous increase in R&D investment, digital infrastructure, and green finance support. The results are shown in Table 2. When R&D investment increases by 10%, the green transformation index increases from 0.612 to 0.648, an increase of 5.88%; when R&D investment increases by 20%, the index increases to 0.684, an increase of 11.76%; and when R&D investment increases by 30%, the index increases to 0.701, an increase of 14.54%. It can be seen that a simple increase in R&D investment exhibits diminishing marginal returns.

Table 2. Policy scenario simulation results.

Scenario	GTI	GTI improvement (%)	Carbon intensity reduction (%)
Baseline	0.612	0.00	0.00
R&D investment +10%	0.648	5.88	4.16
R&D investment +20%	0.684	11.76	8.43
R&D investment +30%	0.701	14.54	9.12
Synergistic improvement	0.712	16.34	10.27

When R&D investment, digital infrastructure, and green finance support are synergistically enhanced, the green transformation index reaches 0.712, an increase of 16.34%, and carbon emission intensity per unit of GDP decreases by 10.27%. This result indicates that technological innovation driving green transformation does not solely rely on expanding R&D investment, but requires the coordinated efforts of digital infrastructure, green finance, and industrial upgrading policies. Digital infrastructure can improve data governance and resource allocation efficiency, while green finance can reduce the cost of green technology transformation for enterprises; the two complement R&D investment.

4.5. Ablation Experiment Results

To verify the effectiveness of each module of TIGT-GA, this paper conducts an ablation experiment. The ablation versions include removing the green constraint attention mechanism, removing the regional correlation graph, removing the technological innovation factor fusion module, and removing the time-series gating module. The results are shown in Table 3. The complete TIGT-GA model has an RMSE of 0.041 and an R^2 of 0.934. After removing the green constraint attention mechanism, the RMSE increases to 0.052, and the R^2 decreases to 0.903, indicating that the green constraint mechanism can effectively improve the model's ability to identify low-carbon development paths. After removing the regional correlation graph, the RMSE rose to 0.061, the highest error among all ablation versions, indicating that technology diffusion, industrial linkages, and energy structure similarities between regions are important information sources in green transition modeling. After removing the technology innovation factor fusion module, the RMSE rose to 0.055, indicating that innovation variables such as R&D investment, patent output, technology transfer, and digital infrastructure play a key role in green transition prediction. After removing the time-series gating module, the RMSE rose to 0.058, indicating that green transition has significant time accumulation and policy lag effects.

Table 3. Ablation experiment results.

Model setting	RMSE	MAE	R^2	Accuracy (%)
Full TIGT-GA	0.041	0.028	0.934	91.6
Without green attention	0.052	0.036	0.903	88.1
Without regional graph	0.061	0.044	0.879	85.2
Without innovation fusion	0.055	0.038	0.896	87.4
Without temporal gate	0.058	0.041	0.887	86.5

5. Conclusion

This paper focuses on the transformation of regional economic green development models driven by technological innovation. It proposes the TIGT-GA green transformation graph attention algorithm and verifies its effectiveness through multi-algorithm comparison experiments, time-series prediction experiments, policy scenario simulation experiments, and ablation experiments. The results show that TIGT-GA can effectively characterize the relationships between regional technology diffusion, industrial linkages, green constraints, and time lags. It outperforms traditional evaluation methods, machine learning methods, and ordinary graph neural network methods in green transformation index prediction, regional level identification, and policy simulation. Experimental results show that TIGT-GA has an RMSE of 0.041, a MAE of 0.028, an R^2 of 0.934, and a level identification accuracy of 91.6%, demonstrating significant advantages over ordinary GAT and XGBoost. Policy simulation results indicate that increased R&D investment can significantly improve the level of regional green transformation, but simply increasing R&D investment exhibits diminishing marginal returns. When R&D investment increased by 20%, the regional green transformation index increased by 11.76%; when R&D investment, digital infrastructure, and green finance support increased synergistically, the regional green transformation index increased by 16.34%, and carbon emission intensity per unit of GDP decreased by 10.27%. This indicates that technological innovation must be synergistic with digital governance, green finance, and industrial structure optimization to more effectively promote the transformation of regional economic green development models. This paper still has some limitations. First, the experimental data is mainly based on regional panel structure simulations, and enterprise micro-innovation data, supply chain transaction data, and real-time carbon emission monitoring data have not been fully incorporated. Second, the policy scenario simulation mainly considers R&D investment, digital infrastructure, and green finance factors, and the characterization of energy price fluctuations, external economic shocks, and supply chain migration is still insufficient. Future research could further introduce enterprise-level innovation data, remote sensing carbon emission data, and multi-agent simulation methods to improve the model's long-term prediction and policy evaluation capabilities for complex regional economic systems.

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