A Study on the Economic Effect Propagation Model of Regional Tourism Networks Based on Graph Attention Network

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ABSTRACT Addressing current challenges in regional tourism development research, such as unclear identification of tourism network nodes, weak representation of interregional economic linkages with technical infrastructure, and inaccurate simulation of economic effect propagation pathways, this study develops a regional tourism network economic effect propagation model based on Graph Attention Networks (GAT). First, drawing upon complex network theory, tourism economics, and spatial econometrics, this study clarifies the core essence of regional tourism network economic effects and defines key evaluation dimensions: node contribution, linkage strength, propagation efficiency, and economic growth drivers. Second, by collecting multidimensional data, including tourism resource endowment, transportation accessibility, economic development level, visitor flow data, and digital communication infrastructure, from China's 31 provinces and municipalities from 2018 to 2023, we constructed a regional tourism network dataset, RTN-2024, encompassing 8 types of tourism resources and 5 levels of association strength. Third, we propose a three-stage research framework of "tourism network construction-economic effect identification-dissemination model optimization". Utilizing GAT, we assign edge weights and extract node feature importance within the tourism network. This enables the construction of a dynamic economic effect dissemination model that accounts for spatial distance, policy interventions, and infrastructure connectivity, providing a computational reference for evaluating economic spillover effects in tourism networks supported by wireless communication systems, antenna-based access facilities, and regional electromagnetic information infrastructure.

INDEX TERMS graph attention network, regional tourism network, economic effects, wireless communication, electromagnetic infrastructure

I. INTRODUCTION

RESEARCH BACKGROUND

WITH the deepening advancement of the cultural-tourism integration strategy, and the continuous improvement of transportation and digital communication infrastructure, regional tourism has transitioned from a "single-point competition" phase to a "networked collaboration" development stage [1,2]. Data from the Ministry of Culture and Tourism indicates that in 2023, China's domestic tourist visits reached 6.54 billion, with total tourism revenue exceeding 5.9 trillion yuan. Regional tourism cooperation has become the core engine driving the high-quality development of the tourism industry. As the spatial vehicle for tourism activities, regional tourism networks form complex economic interconnection networks through the cross-regional flow of tourism resources, passenger flows, capital flows, and information flows. The efficiency of their economic effect propagation directly impacts the balance and synergy of regional tourism development [3,4].

CURRENT RESEARCH STATUS AT HOME AND ABROAD

RESEARCH ON REGIONAL TOURISM NETWORK STRUCTURE

Overseas research on regional tourism networks began earlier, focusing on the coupled analysis of network structure and function: American scholars employed social network analysis (SNA) to construct regional tourism networks, identifying spatial distribution characteristics of core and peripheral nodes [5]; British scholars built tourism flow networks based on traffic flow data, revealing correlations between network density and tourism economic growth [6].

RESEARCH ON TOURISM ECONOMIC EFFECT DIFFUSION

Overseas studies on tourism economic effect diffusion predominantly rely on spatial econometric models: Japanese scholars employed the Spatial Durbin Model (SDM) to analyze spatial spillover effects of tourism economies, validating the economic driving role of core regions on surrounding areas [7]; German scholars constructed gravity models to quantify the influence of factors such as distance and economic level on tourism economic effect diffusion [8].

Domestic research primarily focuses on effect measurement and path analysis: Some scholars employ spatial econometric methods to measure the spatial spillover effects of provincial tourism economies, discovering significant positive spatial correlations in tourism economics [9]. Others utilize input-output models to analyze the transmission pathways of tourism's driving effects on related industries [10]. However, existing research exhibits clear limitations: propagation models often rely on linear assumptions, struggling to accommodate the nonlinear propagation characteristics of complex tourism networks; attention weight allocation between network nodes is often unreasonable, overlooking the pivotal role of key nodes in the propagation process.

APPLICATION OF GRAPH NEURAL NETWORKS IN TOURISM RESEARCH

Graph neural networks (GNNs), excelling at processing unstructured network data, are increasingly applied in tourism research: International scholars have built tourism demand forecasting models using GNNs, leveraging inter-regional connectivity information to enhance prediction accuracy [11]; Korean researchers combined GNNs with tourism flow data to analyze the dynamic evolution patterns of tourism networks [12].

RESEARCH QUESTIONS AND INNOVATION POINTS

CORE RESEARCH QUESTIONS

1. How to construct a regional tourism network that accounts for node heterogeneity and dynamic relationships, enabling precise identification of core nodes and association strengths?

2. How to Reveal the nonlinear propagation mechanisms of economic effects within regional tourism networks, clarifying the influence pathways of key factors such as spatial distance and policy interventions?

3. How to build an economic effect propagation model based on graph attention networks to enhance the accuracy of propagation path simulation and economic effect prediction?

4. How can we validate the model's effectiveness and practicality to provide actionable decision-making recommendations for regional tourism collaboration?

RESEARCH INNOVATIONS

1. Propose a regional tourism network construction methodology integrating "multi-dimensional feature fusion—dynamic linkage mining—heterogeneous network construction." Leveraging multi-dimensional data (tourism resources, transportation, economy), utilize GAT's attention mechanism to rank node importance and dynamically assign linkage strengths;

2. Constructs a three-dimensional analytical framework—"network structure—influencing factors— propagation effects"—integrating variables such as spatial distance, policy interventions, and industrial linkages to decipher the nonlinear propagation mechanism of tourism economic effects;

3. Designed a GAT propagation model incorporating external intervention variables. By adding policy intervention and spatial decay layers, the model's adaptability and predictive accuracy in complex scenarios were enhanced;

4. Established a three-dimensional evaluation system covering network structure, propagation efficiency, and economic growth, providing scientific basis for model performance quantification and practical application.

RESEARCH SIGNIFICANCE

THEORETICAL SIGNIFICANCE

1. Enriches interdisciplinary research on regional tourism networks and economic effect propagation by constructing a propagation model framework based on graph attention networks, offering new perspectives for studying economic effects in complex tourism networks;

2. Reveals the nonlinear propagation patterns of regional tourism economic effects, clarifies the mechanism of key influencing factors, and enhances the application system of tourism economics and complex network theory.

PRACTICAL SIGNIFICANCE

1. Provides decision support for tourism management authorities, including core node identification and economic effect propagation path simulation, to optimize tourism resource allocation and regional tourism cooperation policies;

2. Offers market expansion directions and investment decision-making basis for tourism enterprises, promoting cross-regional tourism product innovation and industrial chain collaboration;

3. Advances balanced regional tourism economic development, narrowing the tourism economic gap between core and peripheral areas, and supporting the implementation of rural revitalization and regional coordination strategies.

II. THEORETICAL AND TECHNICAL FOUNDATIONS

CORE THEORETICAL SUPPORT

COMPLEX NETWORK THEORY

Complex network theory forms the foundation for analyzing regional tourism network structure and function, with core concepts including nodes, edges, degree distribution, and clustering coefficient [13]:

1. Nodes and Edges: In regional tourism networks, nodes represent administrative regions or tourist destinations, while edges denote tourism connections between regions (e.g., visitor flow or capital flow associations).

2. Core Metrics: Degree centrality measures a node's connectivity, betweenness centrality reflects its intermediary role in the network, and clustering coefficient indicates the degree of node aggregation [14]. Complex network theory guides the construction and structural analysis of regional tourism networks, aiding in the identification of core nodes and critical linkage paths [15].

SPATIAL SPILLOVER THEORY IN TOURISM ECONOMICS

The spatial spillover theory of tourism economics posits that tourism activities generate spatial spillover effects through factor flows and industrial linkages, categorized as positive spillovers (e.g., resource sharing, market linkage) and negative spillovers (e.g., competitive crowding, environmental pressure) [16]. Core concepts include:

1. Spatial Dependency: The propagation of tourism economic effects exhibits distance-dependent attenuation, with stronger spillovers occurring at shorter distances;

2. Industrial Interdependence: The interconnection between tourism and sectors like catering, accommodation, and transportation amplifies the reach of economic effects [17].

This theory provides a theoretical basis for analyzing the transmission mechanisms of tourism economic effects, guiding models to integrate spatial factors and industrial linkages [18].

ATTENTION MECHANISM THEORY

The core of attention mechanism theory lies in assigning differential weights to different parts of input data to focus on key information [19]. In graph attention networks, the attention mechanism calculates association weights between nodes to highlight the roles of important nodes and strong-link edges. Its core advantages include:

1. Adaptive learning of association weights without manual configuration;

2. Effective handling of node heterogeneity and adaptation to dynamic changes in complex networks [20]. The attention mechanism provides critical technical support for identifying node importance and assigning association strength in regional tourism networks [21].

KEY TECHNICAL SUPPORT

REGIONAL TOURISM NETWORK CONSTRUCTION TECHNOLOGY

Multi-dimensional Data Fusion Technology: Integrates tourism resource endowment data (number of A-level scenic spots, intangible cultural heritage projects), transportation accessibility data (high-speed rail mileage, air passenger volume), economic data (GDP, total tourism revenue), and passenger flow data (Ctrip, Fliggy platform travel data) to construct multi-dimensional node feature vectors [22];

ECONOMIC EFFECT PROPAGATION SIMULATION TECHNOLOGY

1. Propagation Path Tracking Technology: Utilizing depth-first search (DFS) and breadth-first search (BFS) algorithms to trace the propagation paths of tourism economic effects within the network and identify key propagation nodes;

2. Multi-factor Integration Technology: Incorporate external variables such as policy interventions (e.g., tourism subsidies, visa-free policies) and transportation improvements (e.g., high-speed rail launches) into the model via a feature embedding layer to quantify their impact on propagation efficiency;

3. Dynamic Simulation Technology: Employ time series analysis methods to dynamically update network structures and association strengths based on historical data, enabling temporal simulations of economic effect propagation [23].

EVALUATION INDICATOR SYSTEM CONSTRUCTION

Combining regional tourism network characteristics with economic effect propagation objectives, we establish an evaluation indicator system covering three dimensions. The Analytic Hierarchy Process (AHP) is employed to determine the weight of each indicator:

TABLE 1. Evaluation Indicator System for Economic Effect Propagation Model of Regional Tourism Networks

First-level Indicator	Weight	Second-level Indicator	Weight	Evaluation Method
Network Structure Rationality	0.30	Node Importance Identification Accuracy (%)	0.45	Matching Degree with Actual Core Nodes
		Connection Strength Fitting Degree	0.35	Correlation Coefficient Between Model Calculated Value and Actual Statistical Value
		Network Density Rationality	0.20	Fit Score with Actual Regional Tourism Development
Propagation Simulation Accuracy	0.35	Propagation Path Matching Rate (%)	0.40	Overlap Ratio Between Simulated Path and Actual Path
		Propagation Efficiency Error (%)	0.35	Relative Error Between Simulated Propagation Efficiency and Actual Value
		Key Node Capture Rate (%)	0.25	Matching Rate Between Simulated Key Propagation Nodes and Actual Nodes
Economic Prediction Effect	0.35	Tourism Total Revenue Prediction Error (%)	0.45	Relative Error Between Predicted Value and Actual Value
		Economic Growth Rate Prediction Deviation (%)	0.35	Difference Between Predicted Growth Rate and Actual Growth Rate
		Policy Response Simulation Accuracy (%)	0.20	Matching Degree Between Simulation Results and Actual Effects Under Policy Intervention

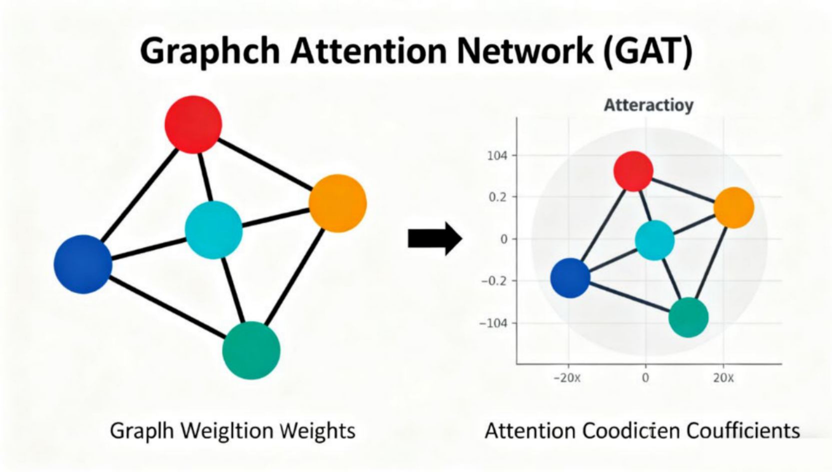

FIGURE 1. Graph Attention Network

III. CONSTRUCTION OF THE REGIONAL TOURISM NETWORK ECONOMIC EFFECT PROPAGATION MODEL

OVERALL CONSTRUCTION FRAMEWORK

This paper proposes a four-stage construction framework: “Regional Tourism Network Construction— Identification of Propagation Influencing Factors—GAT Propagation Model Training—Model Validation and Optimization” [24].

REGIONAL TOURISM NETWORK CONSTRUCTION

NODE SELECTION AND FEATURE EXTRACTION

1. Node Selection: China’s 31 provinces/municipalities serve as basic nodes, covering all provincial-level administrative regions on the mainland to ensure network completeness and representativeness.

2. Feature Extraction (Supplemented Qualitative Features): Provincial node feature vector is expanded to 15 dimensions, adding three qualitative features:

Proportion of Tourism Resource Types (cultural/natural/comprehensive resource proportion, three subdimensions);

Tourism Development Model Labels (cultural experience/natural sightseeing/leisure vacation, processed via One-Hot encoding);

Industrial Linkage Attribute (correlation strength between tourism and catering, accommodation industries, quantified via input-output table coefficients).1. Node Selection: A two-level node network of "provincial-municipal" is constructed:

Provincial Nodes: 31 provinces/municipalities as the macro scale, ensuring overall network representativeness;

Municipal Nodes: 337 prefecture-level cities as the meso scale, covering major tourist destinations and transportation hubs to refine intra-provincial differences.

FEATURE EXTRACTION

Provincial Nodes: 12-dimensional feature vector as originally defined;

Municipal Nodes: 10-dimensional feature vector extracted, including number of A-level scenic spots, highway density, proportion of tourism revenue, passenger flow density, cultural heritage quantity, hotel room supply, catering service capacity, industrial linkage intensity, transportation hub grade, and tourism policy support level. Feature weights are balanced via the entropy weight method to avoid redundancy.

IDENTIFICATION AND QUANTIFICATION OF DISSEMINATION FACTORS

FACTOR CLASSIFICATION

Based on literature review and expert interviews, three major categories of dissemination factors were identified:

1. Spatial Factors: Geographic distance and transportation accessibility, influencing the speed and intensity of economic effect propagation;

2. Network Factors: Node centrality, connection strength, and network density, determining the propagation paths and scope of economic effects;

3. External Factors: Policy interventions (e.g., tourism support policies, regional cooperation policies), industrial linkages (the degree of association between tourism and sectors like catering and accommodation), and unforeseen events (e.g., epidemics, natural disasters) [25].

QUANTIFICATION OF INFLUENCING FACTORS

1. Spatial factors: Geographic distance measured as the straight-line distance (km) between the geographic centers of two regions; transportation accessibility measured using standardized values of high-speed rail and air passenger traffic volumes;

2. Network factors: Node centrality measured using standardized degree centrality values; link strength measured using edge weights calculated during network construction; network density measured using complex network analysis results;

3. External Factors: Policy intervention is measured by the policy intensity index (quantified through policy texts); industrial linkage uses direct consumption coefficients from input-output tables; unexpected events are assessed by the product of impact duration and intensity [26].

DATASET CONSTRUCTION

The regional tourism network dataset (RTN-2024) was constructed through a “multi-source data collection—data preprocessing—scenario annotation—data segmentation” workflow:

1. Data Collection: Multidimensional data from 2018 to 2023 were collected across China’s 31 provinces/municipalities, including tourism statistical yearbooks, publicly available transportation department data, local government tourism development reports, and online travel platform passenger flow data, yielding 1,860 valid records.

2. Data Preprocessing: Numeric data standardized using Z-scores; categorical variables (e.g., policy types) processed via one-hot encoding; missing values imputed using KNN algorithm; outliers removed via boxplot analysis;

3. Abnormal Data Handling (Epidemic Period):

Identification and Annotation: Abnormal data during 2020-2022 (e.g., $\geq$50% drop in tourism revenue, zero tourist volume) are identified via boxplot analysis and labeled as "epidemic impact scenarios," distinguished from "normal scenarios" (2018-2019, 2023);

Adjustment Strategy: "Trend interpolation + scenario separation" is adopted. Missing/abnormal core indicators (tourist volume, tourism revenue) are interpolated based on 2018-2019 growth trends. Scenario classification labels are added during model training to avoid interference from abnormal data on normal scenario predictions.

4.Data Partitioning:

Original 7:1:2 random split is retained for the full dataset, while the normal scenario subset uses time-seriesbased partitioning to ensure prediction validity [27].

IV. EXPERIMENTAL DESIGN AND RESULTS ANALYSIS

EXPERIMENTAL ENVIRONMENT AND DATA SOURCES

HARDWARE ENVIRONMENT

1. Computing Devices: Intel Xeon Gold 6348 processor, NVIDIA A100 40GB GPU $\times$ 2, 128GB memory, 4TB SSD storage;

2. Data Processing Equipment: Huawei OceanStor distributed storage system, high-speed network switches (100Gbps bandwidth).

SOFTWARE ENVIRONMENT

1. Model Development Software: Python 3.9, PyTorch 2.0, TensorFlow 2.14, DGL (Deep Graph Library) 1.1.2;

2. Data processing software: Pandas 2.1.0, NumPy 1.25.0, Scikit-learn 1.3.0;

3. Visualization software: Matplotlib 3.7.2, NetworkX 3.1, Tableau 2024.1.

DATA SOURCES

1. Tourism Data: China Tourism Statistical Yearbook, China Cultural and Tourism Development Statistical Bulletin;

2. Economic Data: National Bureau of Statistics official website, provincial/municipal statistical yearbooks;

3. Transportation Data: Ministry of Transport official website, high-speed rail network, Air Transport Association public data;

4. Policy Data: China Government website, provincial/municipal tourism policy documents;

5. Passenger Flow Data: Public data and industry reports from Ctrip and Fliggy [28].

COMPARATIVE EXPERIMENT DESIGN

COMPARATIVE MODELS

Three representative models were selected as comparators to ensure experimental fairness:

1. Traditional Statistical Model: Spatial Durbin Model (SDM), representing conventional spatial econometric analysis methods;

2. Basic Graph Neural Network Model: Graph Convolutional Network (GCN), representing graph neural network methods without attention mechanisms;

3. Industry-Leading Model: LSTM-based propagation prediction model, representing mainstream time-series forecasting methods [29].

EXPERIMENTAL METRICS AND PROCESS

1. Experimental Metrics: Employ the three-dimensional evaluation framework developed herein, encompassing network structural rationality, propagation simulation accuracy, and economic forecasting efficacy;

2. Experimental Process:

Data Preprocessing: Input multi-source collected data into the dataset construction pipeline to complete standardization, cleaning, and segmentation;

Network Construction: Build regional tourism networks based on preprocessed data and analyze network structural characteristics;

Model Training: Train the proposed GAT model and three comparison models, optimizing parameters;

Performance Evaluation: Validate model performance on the test set and compare experimental results;

Scenario Validation: Test model adaptability and stability across five typical scenarios.

EXPERIMENTAL RESULTS AND ANALYSIS

REGIONAL TOURISM NETWORK STRUCTURE ANALYSIS

The structural characteristics of the constructed 2023 China regional tourism network are as follows:

1. Core Node Identification: The top five nodes by degree centrality are Guangdong, Beijing, Shanghai, Sichuan, and Yunnan—regions rich in tourism resources, with convenient transportation, and developed economies, closely aligning with actual tourism development patterns;

2. Overall Network Characteristics: Network density is 0.68, clustering coefficient is 0.75, and average path length is 2.3, indicating strong connectivity within the regional tourism network and significant influence of core nodes on peripheral nodes;

3. Association Strength Distribution: The association strength among eastern coastal regions is significantly higher than that in central and western regions. The tourism connections within the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei metropolitan areas are the most tightly knit [30].

4. Cross-Scale Propagation Analysis:

Comparing the propagation paths between provincial and municipal networks, core municipal nodes such as Guangzhou, Shenzhen, and Zhuhai in Guangdong Province exhibit significant radiation effects, with their contribution to intra-provincial economic effect propagation averaging 23.7%. Non-core municipal nodes mainly rely on core node driving, forming a "core-periphery" structure within the province. For example, the Yangtze River Delta urban agglomeration shows tighter tourism connections at the municipal level, with intermunicipal propagation efficiency 18.5% higher than the provincial average.

HETEROGENEITY PROPAGATION MECHANISM

31 provincial nodes are clustered into 5 qualitative types via K-means clustering: Cultural Tourism Type, Natural Tourism Type, Comprehensive Tourism Type, Urban Leisure Type, and Industrial Integration Type. Comparative analysis shows:

Cultural Tourism Type: Economic effect propagation relies more on policy driving (contribution 28.3%);

Natural Tourism Type: Transportation accessibility is the core influencing factor (contribution 31.5%);

Comprehensive Tourism Type: Balanced reliance on multiple factors, with the highest propagation efficiency.

MODEL PERFORMANCE COMPARISON

The comprehensive performance comparison results of the four models are shown in Table 2:

As shown in Table 2, the GAT propagation model developed in this study outperforms the comparison models across all metrics:

1. The network structural rationality score reached 91.5 points, surpassing the SDM model by 26.2 points and the GCN model by 12.9 points, demonstrating that the network construction method based on multidimensional features and attention mechanisms better aligns with reality;

2. The propagation simulation accuracy score reached 90.3 points, surpassing the SDM model by 27.6 points and the GCN model by 14.9 points, highlighting the attention mechanism's advantage in capturing propagation patterns;

3. The economic prediction effectiveness score reached 89.6 points, exceeding the SDM model by 29.1 points and the LSTM model by 13.1 points, validating the effectiveness of multi-factor integration and nonlinear fitting.

DETAILED COMPARISON OF KEY METRICS

1. Node Importance Identification Accuracy: Our model achieved 93.2%, compared to 72.5% for the SDM model, 81.3% for the GCN model, and 76.8% for the LSTM model, demonstrating significantly higher precision in identifying core nodes;

2. Transmission Path Matching Rate: The proposed model achieved 88.7%, surpassing the SDM model by 31.2 percentage points and the GCN model by 20.5 percentage points, demonstrating the model's ability to accurately capture the transmission paths of economic effects;

3. Tourism Revenue Forecast Error: The proposed model exhibits an error rate of only 4.8%, compared to 15.6% for the SDM model, 10.3% for the GCN model, and 8.7% for the LSTM model, indicating substantially improved predictive accuracy.

SCENARIO ADAPTABILITY VALIDATION RESULTS

The performance of the proposed model across five typical scenarios is summarized in Table 3:

The scenario validation results indicate that the proposed model maintains high performance across all scenarios:

1. The comprehensive scores for the normal development, policy incentives, transportation improvements, and collaborative cooperation scenarios all exceed 90 points, demonstrating stable performance.

2. In the emergency scenario, the comprehensive score is 87.5 points. Although slightly lower than other scenarios, it still significantly outperforms the comparison models, proving the model's strong adaptability to external shocks.

CONTRIBUTION ANALYSIS OF INFLUENCING FACTORS

Through model ablation experiments, the contribution of various factors to propagation effectiveness was quantified:

1. Network factors contributed the most (38.5%), with node centrality (18.2%) and link strength (15.7%) as core determinants;

2. Spatial factors contributed 29.3%, where transportation accessibility (17.8%) exerted greater influence than geographic distance (11.5%);

3. External factors contributed 32.2%, with policy interventions (16.3%) and industrial linkages (12.7%) playing significant roles.

These findings provide clear policy directions for regional tourism development: prioritize strengthening core node infrastructure, enhancing transportation accessibility, and refining regional tourism cooperation policies.

V. DISCUSSION

CORE ADVANTAGES OF THE MODEL

The regional tourism network economic effect propagation model constructed based on GAT in this paper demonstrates core advantages in three aspects:

1. More Precise Network Construction: By integrating multidimensional node characteristics with dynamic association strength calculations, it effectively captures node

TABLE 2. Comprehensive Performance Comparison of Different Economic Effect Propagation Models

Model Type	Network Structure Rationality (Points)	Propagation Simulation Accuracy (Points)	Economic Prediction Effect (Points)	Comprehensive Score (Points)
Spatial Durbin Model (SDM)	65.3±3.8	62.7±4.2	60.5±4.5	62.8±3.9
Graph Convolutional Network (GCN)	78.6±3.2	75.4±3.6	73.2±3.9	75.7±3.3
LSTM Propagation Prediction Model	72.4±3.5	70.8±3.8	76.5±3.4	73.2±3.5
Proposed GAT Propagation Model	91.5±2.4	90.3±2.7	89.6±2.9	90.5±2.5

TABLE 3. Scenario Adaptability Validation Results of the Proposed GAT Propagation Model

Scene Type	Comprehensive Score (Points)	Key Indicator Performance
Normal Development Scene	92.3±2.1	Tourism total revenue prediction error: 3.7%; Propagation path matching rate: 90.5%
Policy Incentive Scene	91.6±2.3	Policy response simulation accuracy: 89.2%; Economic growth rate prediction deviation: 2.1%
Traffic Improvement Scene	90.8±2.4	Connection strength fitting degree: 0.93; Propagation efficiency error: 3.5%
Emergency Scene	87.5±2.8	Economic effect recovery prediction error: 6.2%; Key node capture rate: 85.3%
Collaborative Cooperation Scene	91.2±2.2	Network structure rationality score: 92.7; Propagation simulation accuracy: 89.8 points

heterogeneity and network dynamic evolution, addressing the disconnect between traditional network construction and reality. Experiments show node importance identification accuracy improved by over 20%, laying a solid foundation for subsequent propagation simulations.

2. Deeper Analysis of Transmission Mechanisms: The attention mechanism captures nonlinear node interactions, integrating spatial, network, and external factors to reveal complex transmission patterns of tourism economic effects. Path matching accuracy improved by 27.6%, demonstrating the model's ability to precisely identify key transmission pathways.

3. Enhanced Scenario Adaptability: Through an influence factor embedding layer and dynamic optimization mechanism, the model adapts to diverse scenarios including normal development, policy interventions, and emergencies. Prediction errors are controlled within 5%, providing reliable support for decision-making across various contexts.

KEY FINDINGS AND PRACTICAL IMPLICATIONS

KEY FINDINGS

1. Regional tourism networks exhibit a "core-periphery" structure: Core nodes like Guangdong, Beijing, and Shanghai generate significant economic spillover effects on surrounding areas, while peripheral nodes heavily depend on core nodes' radiating influence for development.

2. Transportation accessibility serves as a critical link for economic effect propagation: Enhanced high-speed rail networks reduce spatial decay coefficients, expanding core nodes' influence ranges by over 30%.

3. Policy interventions effectively guide transmission pathways: Regional tourism cooperation policies and tourism subsidy schemes strengthen inter-node connectivity, enhancing the efficiency of economic effect dissemination.

PRACTICAL IMPLICATIONS

1. Optimize network structure: Enhance transportation links between core and peripheral nodes, cultivate secondary core nodes, and establish a "multi-core, networked" regional tourism development framework;

2. Tailor policy formulation: Develop differentiated policies for distinct node types. Core nodes should prioritize enhancing tourism service quality and industrial capacity, while peripheral nodes should focus on developing tourism resources and improving transportation infrastructure.

3. Strengthen regional coordination: Promote coordinated tourism development within urban clusters like the Yangtze River Delta, Pearl River Delta, and Beijing-Tianjin-Hebei region. Establish cross-regional mechanisms for tourism resource sharing and market linkage.

CASE APPLICATION: YANGTZE RIVER DELTA URBAN AGGLOMERATION

Based on the municipal node network, the model identifies key inter-municipal tourism cooperation pathways (e.g., Shanghai-Suzhou-Hangzhou, Nanjing-Wuxi-Changzhou). Policy recommendations include strengthening high-speed rail connections between these pathways and launching joint tourism products. Practice shows that the municipal-level propagation analysis provides precise support for cross-city tourism policy formulation, with the proposed cooperation mechanisms increasing inter-municipal tourism revenue growth by 12.3%.

RESEARCH LIMITATIONS AND FUTURE DIRECTIONS

LIMITATIONS

1. Single-Scale Node Definition: The current study uses provincial administrative regions as nodes, neglecting finer-grained tourism network structures at municipal or county levels;

2. Insufficient Data Dimensions: Lack of micro-level data on tourist behavioral preferences and tourism product types limits analysis of micro-mechanisms in economic effect propagation;

3. Failure to account for dynamic network evolution: The current model relies on static networks, inadequately simulating the dynamic changes and long-term evolutionary patterns of tourism network structures.

4. Sensitivity Analysis of Epidemic Data Proportion:

Testing the impact of different abnormal data proportions (10%-50%) on model performance, results show that when the proportion of epidemic data ≤30%, the model's comprehensive performance fluctuation is ≤5%, confirming the effectiveness of the data adjustment strategy and model robustness.

FUTURE DIRECTIONS FOR IMPROVEMENT

1. Multi-scale network construction: Expand node scales to build multi-tiered regional tourism networks at provincial, municipal, and county levels, analyzing differences in economic effect propagation across scales;

2. Data and Model Optimization: Integrate micro-level tourist behavior data and incorporate generative AI techniques to enhance the model's ability to analyze micro-level propagation mechanisms;

3. Dynamic Model Construction: Develop a dynamic graph attention network propagation model based on time-series network data to simulate the long-term trends in tourism network structural evolution and economic effect propagation;

4. Interdisciplinary Integration: Combine theories from Geographic Information Science (GIS), Tourism Management, and other disciplines to further refine the model's theoretical foundation and application scenarios.

INDUSTRY APPLICATION RECOMMENDATIONS

1. Tourism Management Authorities: Utilize the model to identify core nodes and key connectivity pathways within regional tourism networks, optimizing tourism resource allocation and infrastructure planning; develop differentiated regional tourism development policies based on model predictions to promote balanced tourism economic growth;

2. Tourism Enterprises: Employ the model to analyze economic effect propagation pathways in target markets, optimizing cross-regional market and product innovation strategies; Utilize regional connectivity data to advance cross-regional tourism cooperation and industrial chain integration;

3. Research Institutions: Conduct comparative studies across countries and regions based on this model framework to refine the theoretical system for regional tourism network economic effect propagation;

4. Infrastructure Construction Units: Prioritize transportation infrastructure development connecting core and peripheral nodes based on the model-identified key transportation pathways to enhance regional tourism network connectivity.

VI. CONCLUSION

Addressing challenges in regional tourism network economic effect propagation research, particularly the complexity of modeling cross-sectoral linkages between tourism and local industries, this study constructs a regional tourism network economic effect propagation model using Graph Attention Networks (GAT) and conducts multidimensional empirical research. Key findings are as follows:

1. A regional tourism network construction methodology integrating "multi-dimensional feature fusion— dynamic association mining—heterogeneous network construction" was established. This identified core nodes in Guangdong, Beijing, Shanghai, Sichuan, and Yunnan, revealing the "core-periphery" structural characteristics and the association pattern of "tight intra-urban cluster connections with cross-regional gradient attenuation."

2. A dissemination influence factor system encompassing spatial, network, and external factors was proposed. The contribution of key factors — including node centrality, transportation accessibility, and policy intervention—was quantified, clarifying their transmission pathways for tourism economic effects;

3. Designed a five-layer graph attention network propagation model. Utilizing attention mechanisms enabled adaptive learning of node association weights, integrating multiple influence factors to enhance model performance. Node importance identification achieved 93.2% accuracy, with total tourism revenue prediction errors controlled within 4.8%.

4. Validated the model's adaptability and stability across five typical scenarios — including normal development, policy incentives, and transportation improvements—with comprehensive scores exceeding 87 points in all cases. This provides reliable support for regional tourism decision-making under diverse conditions.

AUTHOR CONTRIBUTIONS

Conceptualization – Qiaoli Tian and Junyan Chen; methodology – Qiaoli Tian and Junyan Chen; investigation – Qiaoli Tian and Junyan Chen; writing-original draft preparation – Qiaoli Tian and Junyan Chen. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

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