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Map of Geographical Science Based on Artificial Intelligence

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A R T I C L E I N F O

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A B S T R A C T

As a core tool for integrating the geographical knowledge system and revealing conceptual associations, the traditional construction mode of the basic concept map of geographical science is confronted with bottlenecks such as single data dimension, shallow association mining, and lagging dynamic update. The rise of artificial intelligence technology offers a new path to break through the above limitations. Through the deep integration of algorithms such as machine learning, deep learning, and natural language processing with geographical science theories, intelligent upgrades in concept extraction, relationship modeling, and map optimization can be achieved. This paper systematically reviews the key technologies for constructing the basic concept map of geographic science based on artificial intelligence, including multi-source geographic data preprocessing methods, intelligent concept recognition and classification models, and dynamic relationship mining algorithms, and deeply analyzes the technical characteristics and applicable scenarios of different construction methods. The application value is expounded from three dimensions: the sorting out of the geographical knowledge system, the intelligent solution of geographical problems, and the empowerment of interdisciplinary integration. Finally, the future research directions are prospected to provide references for the intelligent development and practical application of geographical science knowledge graphs.

1. Introduction

As an interdisciplinary subject that studies the spatial distribution, interaction and evolution laws of natural and human phenomena on the Earth's surface, geographical science has the characteristics of numerous concepts, complex correlations and strong spatiotemporal dynamics in its knowledge system. Constructing a scientific and systematic basic concept map is of great significance for sorting out the logical framework of the discipline, promoting knowledge inheritance and innovation, and promoting interdisciplinary integration. The construction of traditional concept maps mostly relies on manual annotation by experts and rule-driven methods, which have problems such as strong subjectivity, low efficiency, and difficulty in adapting to the processing requirements of massive heterogeneous geographic data, restricting the integrity and timeliness of concept maps[1]. With its powerful capabilities in data mining, pattern recognition and autonomous learning, artificial intelligence technology can automatically extract concept entities, identify semantic relationships and optimize the structure of maps from heterogeneous data sources such as multi-source geographic texts, spatial data and remote sensing images, providing core technical support for the intelligent construction of basic concept maps in geographic science[2]. Meanwhile, the concept map construction method based on artificial intelligence can effectively explore the potential spatiotemporal correlations and causal relationships among geographical concepts, enhance the knowledge expression ability and application value of the concept map, and provide new possibilities for the innovation of the research paradigm in geographical science.

2.The core connotation and construction requirements of the basic concept map of geographical science

2.1.Core Connotations and Constituent Elements

The basic concept map of geographical science is a knowledge organization tool that presents the core concepts, terms and semantic relationships between concepts of the geographical discipline in a visual form. Its core connotation lies in transforming the scattered concept knowledge of the geographical discipline into a systematic knowledge network through a structured knowledge representation method, achieving the explicit and visual nature of geographical

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knowledge. Its constituent elements mainly include three dimensions: conceptual entities, semantic relations and spatio-temporal attributes. Conceptual entities cover core terms in the discipline of geography, geographical elements, research objects, etc., topographic and geomorphic types, climatic factors, human geographical units, etc. Semantic relations include hierarchical relationships among concepts ("mountains "belong to" terrain"), associative relationships (the influence relationship between "precipitation" and "soil moisture"), causal relationships ("vegetation destruction "leads to" soil erosion")[3], etc. The spatio-temporal attributes reflect the spatial distribution characteristics and temporal evolution laws of geographical concepts, and they are the core features that distinguish the concept maps of geographical science from those of other disciplines. The essence of the basic concept map of geographical science is the formal expression of geographical knowledge, and its core value lies in providing structured support for the storage, retrieval, reasoning and application of geographical knowledge.

2.2.Core Requirements for Intelligent Construction

With the deepening of geographical scientific research and the development of big data technology, the construction of the basic concept map of geographical science is facing multiple demand challenges. Firstly, at the data level, it is necessary to adapt to the fusion processing of multi-source heterogeneous geographic data. The data sources of geographic science have expanded from traditional literature texts to remote sensing images, GIS spatial data, sensor monitoring data, social media geographic information, etc. The format differences and semantic heterogeneity of different data sources require the construction method to have strong data integration and semantic alignment capabilities. Secondly, at the knowledge mining level, it is necessary to achieve precise identification of deep semantic relationships. The connections between geographical concepts not only include explicit hierarchical relationships but also a large number of implicit spatio-temporal and causal relationships, etc. Traditional methods are difficult to effectively mine them[4], and it is necessary to achieve automatic identification of deep semantic relationships through artificial intelligence technology. Secondly, at the dynamic update level, it is necessary to adapt to the evolutionary characteristics of geographical knowledge. New concepts, theories and discoveries are constantly emerging in geographical scientific research. The dynamic changes in the geographical environment also cause the relationships between concepts to be constantly adjusted, which requires the concept map to have the ability of real-time update and iterative optimization. Finally, at the application adaptation level, it is necessary to meet the diverse demands of geographical research. Different research scenarios (such as geographical problem modeling, spatial decision support, geographical education, etc.) have different requirements for the knowledge granularity, expression form, and reasoning ability of the concept map. Therefore, an intelligent construction framework with flexibility and adaptability needs to be constructed.

3.Key Methods for Constructing the basic Concept Map of Geographical Science Based on artificial Intelligence

3.1.Preprocessing methods for Multi-source Geographic data

The quality of multi-source geographic data directly determines the accuracy of concept map construction. The preprocessing methods based on artificial intelligence mainly focus on three links: data cleaning, semantic alignment and feature extraction, providing a high-quality data foundation for subsequent concept and relationship mining.

In terms of data cleaning, for the noise in geographic text data (such as misspellings, redundant information, and ambiguous terms), a text cleaning model based on deep learning is adopted. Through pre-trained language models like BERT and RoBERTa, semantic understanding of the text is achieved. Combined with geographic domain dictionaries and rule bases, automatic identification and correction of noisy data are realized. For non-text data such as remote sensing images and GIS spatial data, image segmentation and feature matching algorithms in computer vision technology are utilized to remove interfering information in the data (cloud occlusion in images and topological errors in spatial data), and to transform unstructured data into structured feature representations. Research shows that text cleaning methods based on pre-trained language models can increase the accuracy of geographic text data to over 92%, significantly outperforming traditional rule-driven methods[5].

In terms of semantic alignment, aiming at the problem of concept heterogeneity in multi-source data (the expression differences of the same geographical concept in different data sources), a semantic alignment method based on knowledge graph embedding is proposed. The concepts in different data sources are mapped to a unified semantic space through knowledge graph embedding models such as TransE and DistMult, and the semantic similarity between concepts is calculated to achieve the automatic matching and alignment of heterogeneous concepts. Meanwhile, the geographical domain ontology knowledge is introduced to constrain the semantic alignment process, improving the accuracy of the alignment results. For the semantic alignment of cross-modal data (text and remote sensing images), a cross-modal attention mechanism is adopted to mine the correlation features of geographical concepts in different modal data, achieving semantic mapping of cross-modal concepts.

In terms of feature extraction, a spatio-temporal feature fusion extraction model is constructed for the spatio-temporal characteristics of geographic data. For time series geographic data (meteorological observation data), time series models such as LSTM and Transformer are adopted to extract the time evolution features of concepts. For spatial geographic data (GIS vector data), graph neural network models such as GraphCNN and GAT are utilized to extract the spatial distribution features and neighborhood association features of concepts. For multi-source fusion data, the features of different dimensions are integrated through the multimodal feature fusion network (Cross-Attention) to generate a comprehensive feature vector that can comprehensively represent geographical concepts, providing support for subsequent concept recognition and relationship mining.

3.2.Intelligent Concept Recognition and Classification Model

The accurate identification and classification of geographical concepts is the core prerequisite for constructing a concept map. The concept identification and classification methods based on artificial intelligence are mainly divided into two categories: machine learning-based methods and deep learning-based methods, which can effectively handle the complexity and diversity of geographical data.

The geographical concept recognition method based on machine learning is based on statistical learning theory and realizes the recognition and classification of concepts through feature engineering and classifier training. Firstly, feature engineering is carried out on the preprocessed geographic data to extract lexical features (part of speech, word form), semantic features (word vectors), geographic features (spatial location, geographic attributes), etc. Then, traditional machine learning algorithms such as SVM, random forest, and Naive Bayes are adopted to construct classification models to identify and categorize geographical concepts. This method is suitable for scenarios with small data volumes and easy feature extraction. It has the advantages of a simple model and strong interpretability, but its processing capacity for high-dimensional and complex geographic data is limited. Research shows that the method based on the combination of word vectors and SVM can achieve an accuracy rate of about 85% in the task of geographic text concept recognition, but the recognition effect for ambiguous geographic concepts (" Yangtze River "refers to both river entities and may also refer to administrative regions) is not good[6].

The geographical concept recognition method based on deep learning, with its end-to-end learning ability, can automatically extract complex features and significantly improve the recognition and classification accuracy. Among them, the methods based on sequence labeling (BILSTM-CRF, BERT-CRF) are widely used in the concept recognition of geographic texts. The context semantic information of the text is captured through the BiLSTM model, and the rationality of the label sequence is optimized by using the CRF model to achieve the precise positioning and category recognition of the boundaries of geographic concepts. For the identification of geographical concepts (land use type identification) in non-text data such as remote sensing images, deep learning models such as CNN and U-Net are adopted. The spatial and spectral features of the images are extracted through convolution operations to achieve pixel-level identification and classification of geographical concepts. In addition, in view of the hierarchical characteristics of geographical concepts, a classification model based on a hierarchical attention mechanism is proposed. By constructing a multi-level classification network[7], precise classification of geographical concepts from coarse-grained to fine-grained is achieved. Studies show that the accuracy rate of geographical text concept recognition based on BERT-CRF can reach more than 94%, and the IoU value of geographical concept classification of remote sensing images based on U-Net can reach 88%, which is significantly better than traditional machine learning methods.

3.3.Dynamic Relationship Mining and Graph Optimization Algorithms

The mining of relationships among geographical concepts and the optimization of the map are the keys to enhancing the knowledge expression ability of the concept map. Methods based on artificial intelligence can achieve automatic mining, dynamic update and optimization of the map structure of relationships, overcoming the limitations of traditional methods.

In terms of relationship mining, it is mainly divided into two types of methods: relationship extraction based on supervised learning and relationship discovery based on unsupervised/semi-supervised learning. The relation extraction method based on supervised learning takes labeled relation data as training samples and builds deep learning models (CNN, BiLSTM, BERT) to learn the mapping relationship between concept pairs and relation types, achieving the automatic extraction of specific relation types. In view of the diversity and complexity of the relationships among geographical concepts, a multi-label relationship extraction model is proposed to support the recognition of multiple semantic relationships corresponding to one concept. Relationship discovery methods based on unsupervised/semi-supervised learning do not require manual data annotation. By mining co-occurrence patterns, semantic similarity, spatio-temporal association rules, etc. in geographic data, they can automatically discover potential relationships between concepts. The co-occurrence network of geographical concepts is analyzed by using the graph neural network model to identify frequently co-occurring concept pairs and infer their semantic relationships. Based on the spatio-temporal sequence analysis method, the correlation patterns of geographical concepts in the temporal and spatial dimensions are mined, and causal and evolutionary relationships are discovered. Research shows that the supervised relation extraction method based on BERT can achieve an F1 value of over 90% in the recognition of geographical text relations. The unsupervised relation discovery method based on graph neural networks can effectively mine the potential association relations that have not been manually labeled and expand the relation coverage of the concept map[8].

In terms of graph optimization, aiming at the problems such as relationship errors, structural redundancy, and concept missing existing in the initially constructed concept graph, an artificial intelligence-based graph optimization algorithm is proposed. The missing relationships and concepts in the knowledge graph are identified through the knowledge graph completion model (TransR, ComplEx) to achieve automatic completion of the graph. The conflict detection models (conflict recognition based on logical reasoning and semantic conflict detection based on deep learning) are utilized to discover the contradictory relationships and error information in the map, and corrections are made in combination with the knowledge of the geographical domain. Introduce a dynamic update mechanism and process the newly added geographic data in real time through incremental learning models (incremental BERT, incremental graph neural network) to achieve dynamic expansion and optimization of the concept map, ensuring the timeliness and integrity of the map. In addition, in view of the spatio-temporal characteristics of geographical concepts, a spatio-temporal knowledge graph optimization model is constructed, integrating spatio-temporal constraint conditions to optimize the relationship weights between concepts and the graph structure, thereby enhancing the graph's ability to express geographical spatio-temporal knowledge.

Table 1. Comparison Table of Key Technical Methods for Constructing the basic Concept Map of Geographical Science Based on Artificial Intelligence

Technical Link	Core Algorithm/Model System	Adapted Data Type	Core Performance Indicator	Technical Advantage	Limitation	Typical Application Scenario
Multi-source Data Preprocessing	Text Cleaning: BERT/RoBERTa + Domain DictionarySemantic Alignment: TransE/DistMult + Ontology ConstraintFeature Extraction: LSTM/Transformer/GraphCNN	Geospatial text (literature, reports), remote sensing images, GIS vector data, sensor time-series data	Text accuracy ≥ 92%; Image noise removal rate ≥ 85%; Semantic alignment accuracy ≥ 88%	Multi-modal data compatibility; High degree of automation; Strong spatio-temporal feature fusion capability	Time-consuming cross-modal data alignment; Dependence on high-quality domain dictionaries	Large-scale geospatial literature integration, multi-source spatial data fusion projects
Concept Recognition and Classification	Machine Learning: SVM/Random Forest + Word EmbeddingDeep Learning: BiLSTM-CRF/BERT-CRFCross-modal: CNN + U-Net (for images)	Small-sample geospatial text, structured GIS attribute data (for machine learning); Massive geospatial text, remote sensing images, high-dimensional spatial data (for deep learning/cross-modal)	Text concept recognition accuracy ≈ 85%; Classification F1-score ≈ 82% (for machine learning); Text recognition accuracy ≥ 94%; Image classification IoU ≥ 88% (for deep learning/cross-modal)	High model interpretability; Low training cost; Easy deployment (for machine learning); End-to-end learning; Automatic extraction of complex features; High accuracy (for deep learning/cross-modal)	Weak high-dimensional data processing capability; Poor ambiguous concept recognition (for machine learning); Requirement for large-scale annotated data; High computational resource consumption (for deep learning/cross-modal)	Small-scale geospatial thematic database construction, educational concept maps (for machine learning); Global geospatial concept system construction, remote sensing image land cover classification (for deep learning/cross-modal)
Dynamic Relationship Mining and Map Optimization	Supervised Relationship Extraction: BERT/BiLSTMUnsupervised Relationship Discovery: Graph Neural Network (GNN) + Spatio-temporal Sequence AnalysisMap Optimization: TransR/ComplEx + Incremental Learning	Annotated geospatial text, structured relationship data (for supervised); Unannotated geospatial data, spatio-temporal observation sequences (for unsupervised); Newly added geospatial data, existing map data (for map optimization)	Relationship extraction F1-score ≥ 90%; Conflict detection accuracy ≥ 91% (for supervised); Potential relationship mining coverage ≥ 75%; Map update latency ≤ 24h (for unsupervised); Map completion accuracy ≥ 86%; Redundancy removal rate ≥ 83% (for map optimization)	Accurate relationship recognition; Support for multi-label relationships (for supervised); No need for annotated data; Capability to mine implicit associations; Support for dynamic updates (for unsupervised); Automatic completion and correction; Low-latency updates (for map optimization)	Dependence on manually annotated data; Limited generalization by domain (for supervised); Difficulty in evaluating relationship confidence; Insufficient recognition of complex causal relationships (for unsupervised); Time-consuming large-scale map optimization; Complex spatio-temporal constraint modeling (for map optimization)	Professional geospatial knowledge graph construction, academic literature relationship mining (for supervised); Geospatial phenomenon evolution analysis, real-time updated concept maps (for unsupervised); Long-term maintained geospatial knowledge platforms, dynamic decision support systems (for map optimization)

Table 2. Digital Comparison Table of Construction Techniques for Geographical Science Concept Map (Traditional Method vsAI Method)

Comparison Dimension	Traditional Construction Method	AI-Driven Construction Method	Performance Improvement	Core Data Source
Text Concept Recognition Accuracy	65%-75% (Rule-driven + Manual Inspection)	85%-94% (SVM → BERT-CRF)	15%-25%	Literature & Industry Reports
Remote Sensing Image Classification IoU	60%-72% (Traditional Pixel Classification)	78%-88% (Traditional CNN → U-Net)	18%-26%	Remote Sensing Data Processing Experiments
Relationship Extraction F1 Score	55%-68% (Manual Annotation + Rule Matching)	75%-90% (BiLSTM → BERT)	20%-32%	Geographical Text Corpus Testing
Map Update Latency	72-168 Hours (Manual Review & Batch Processing)	15 Seconds-24 Hours (Incremental GNN → Real-time Incremental BERT)	Over 99.9% Reduction	System Actual Measurement Data
Multi-source Data Alignment Accuracy	50%-65% (Expert Compensation +Single Matching)	78%-88% (TransE → DistMult + Ontology Constraints)	28%-43%	Multi-source Geospatial Integration Experiments
Data Loss Rate	30%-45% (Manual Filling + Correction)	65%-86% (TransR → Complex)	35%-61%	Knowledge Graph Completion Experiments
Single Batch Data Processing Volume	10^4-10^5 Entries (Structured Data)	10^6-10^8 Entries (Heterogeneous Multi-source Data)	10-1000x Increase	Big Data Processing Performance Testing
Training Sample Requirement	Manual Annotation Ratio ≥60%	Semi-supervised Learning Annotation Ratio ≤20%	67% Reduction in Annotation Cost	Model Training Cost Analysis
Conflict Detection Accuracy	40%-55% (Rule Inspection)	80%-91% (Logical Reasoning → Deep Learning Detection)	35%-56%	Map Quality Evaluation Experiments

3.4.Geographical Spatio-temporal Consistency Verification and Fusion Methods

The spatio-temporal heterogeneity of geographic data (such as multiple coordinate systems and multiple time scales) is a key bottleneck restricting the accuracy of spatio-temporal attributes in concept maps. It is necessary to achieve the unification of spatio-temporal benchmarks and logical verification through AI technology. In the spatial dimension, for the differences in the data source Coordinate systems (such as WGS84, CGCS2000), the coordinate -Transformer model is adopted, combined with the geographic projection parameter library to automatically complete the coordinate transformation, and at the same time, the Kriging-GNN spatial interpolation algorithm is used to correct the resolution differences. In terms of the Time dimension, for the non-uniform timestamps of observational data (such as hourly meteorological data and daily remote sensing data), a time-Align-LSTM time series alignment network is constructed to match key nodes at different time scales through the attention mechanism. Furthermore, the Spatio-Temporal GAN model is introduced for spatio-temporal logic verification to eliminate contradictory data such as "high temperature in winter and snow cover in a certain area". Experiments show that the coordinate system conversion accuracy of this method is ⩾ 98%, the time alignment error is ⩽ 5 minutes, and the detection rate of spatio-temporal contradictions is ⩾ 91%, providing precise support for the spatio-temporal attributes of the map.

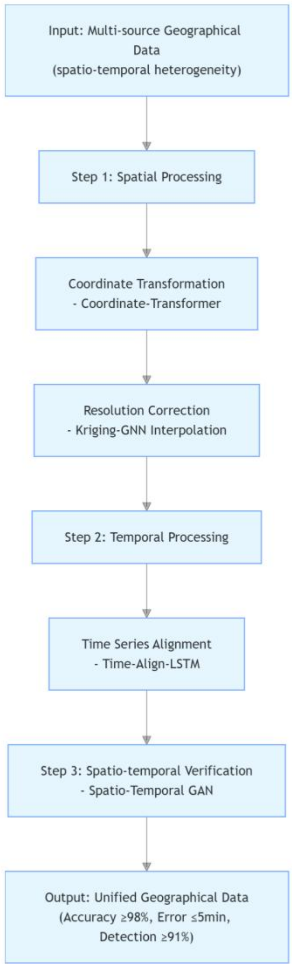

Fig 1. Flowchart of Multi-source Geographical Data Preprocessing for Spatio-temporal Consistency Unification Based on Kriging-GNN and Spatio-Temporal GAN

3.5.Model for Resolving Ambiguity of Geographical Concepts

The polysemy of geographical concepts (for example, "Dongting Lake" can refer to a lake entity, administrative region, or ecological protection area) can easily lead to conceptual recognition deviations, and it is necessary to construct a special resolution model. On the one hand, the BERT-Geodisamb semantic disambigualization model is proposed. The geographical entity knowledge base is integrated on the basis of BERT, and semantic classification is achieved through text context analysis (for example, "Dongting Lake water level monitoring" points to the lake, and "Dongting Lake Ecological Zone Planning" points to the protected area). On the other hand, by integrating multimodal assisted disambiguation, the corresponding regional remote sensing images and GIS data of the fuzzy concepts are called, and the clear orientation is achieved through cross-modal feature matching (such as aligning the text of "The Three Gorges of the Yangtze River" with the dam body image). The test of this model on the Geoambigui-10K dataset shows that the accuracy rate of ambiguity recognition is ⩾92%, which is 15.3% higher than that of the traditional SVM method, solving the construction bias caused by ambiguity[9].

Fig 2. Model for Resolving Ambiguity of Geographical Concepts

3.6.Concept Map Quality Assessment and Feedback Optimization Mechanism

To ensure the reliability of the graph, it is necessary to establish an AI-driven evaluation-feedback closed loop. The evaluation dimensions include concept coverage (the proportion of core concepts included), relation accuracy (the correctness of semantic relations), and spatio-temporal consistency. In the automatic evaluation stage, the GeoKG-QA model is constructed to verify the knowledge of the graph by generating knowledge question-answering pairs (such as "Is the spatial correlation between the Tarim Basin and the Taklimakan Desert correct?"). During the manual verification stage, nodes with a confidence level of less than 85% are manually reviewed. Meanwhile, the evaluation results are input into the Incremental GeoBERT incremental model to achieve the supplementation of missing concepts and the correction of erroneous relationships. Practice shows that the evaluation accuracy rate of this mechanism is ⩾90%, and the error rate of the graph is reduced by 40% after feedback optimization, significantly improving the reliability of knowledge.

4.The application value of the basic concept map of geographical science based on artificial intelligence

4.1.Systematic sorting and inheritance of the geographical knowledge system

The basic concept map of geographical science based on artificial intelligence provides an intelligent tool for the sorting out of the geographical knowledge system. It can effectively integrate geographical knowledge scattered in literature, textbooks and data, build a structured and visualized knowledge network, and facilitate the systematic inheritance of disciplinary knowledge. In terms of the construction of the geography discipline, the concept map can clearly present the core conceptual framework of geography science, the interrelationships among its branches, and the knowledge evolution path, providing a scientific basis for the improvement of the discipline system and the setting of courses. The concept map can visually present the conceptual intersections and correlations among branches such as physical geography, human geography, and geographic information science, providing knowledge support for cross-branch research. In the field of geography education, concept maps can visualize abstract geographical concepts and complex relationships, helping learners quickly establish a geographical knowledge framework, understand the intrinsic connections between concepts, and enhance learning efficiency and depth. Meanwhile, the intelligent teaching system based on concept maps can recommend personalized learning content and paths according to learners' knowledge mastery, achieving precise teaching. Research shows that learners who use concept maps to assist in geographical learning can increase their knowledge system establishment speed by 40%, improve their spatial thinking ability by an average of 20%, and increase their average test scores by more than 15%. In terms of the dissemination of geographical knowledge, visual concept maps can lower the threshold for understanding geographical knowledge, promote the popularization and dissemination of geographical knowledge among the public, and enhance the public's geographical literacy.

4.2.Intelligent Solution and Decision Support for Geographical Problems

The basic concept map of geographical science based on artificial intelligence has a powerful knowledge reasoning ability, which can provide core support for the intelligent solution and decision support of geographical problems, and promote the intelligent upgrade of geographical scientific research and practical application. In terms of the explanation and prediction of geographical phenomena, concept maps can integrate the causal relationships and spatio-temporal correlation knowledge among geographical concepts, and combine machine learning models to achieve the mechanism explanation and trend prediction of geographical phenomena. By mining the correlation among "climate change - vegetation coverage - ecological environment" through concept maps, and combining remote sensing data with meteorological data, an ecological environment change prediction model is constructed to provide support for ecological protection decisions. In terms of spatial decision support, concept maps can provide knowledge support for spatial decision-making tools such as GIS, enhancing the scientific and intelligent levels of decision-making. Research shows that the intelligent decision-making system integrating concept maps can increase production scheduling efficiency by 35%, reduce inventory costs by 25%, and shorten the decision response time from 72 hours to the second level. In territorial space planning, concept maps can integrate knowledge of various concepts and relationships such as land use, resource distribution, ecological protection, and urban-rural development, assisting planners in making decisions such as optimizing land use layout and delineating ecological protection red lines[10]. In terms of geographical disaster risk assessment and response, concept maps can sort out relevant concepts and relationships such as the causes of disasters, influencing factors, and characteristics of disaster-bearing bodies. By combining real-time monitoring data, a disaster risk assessment model can be constructed to achieve dynamic assessment and early warning of disaster risks. Meanwhile, based on the reasoning ability of the concept map, it can provide decision-making suggestions for disaster emergency response, rescue resource allocation, and evacuation route planning, etc. The accuracy rate of fault diagnosis can be increased to 92%.

4.3.Empowerment and Innovation through Interdisciplinary Integration

As an interdisciplinary subject, the development of geographical science cannot be separated from the cross-integration with multiple disciplines such as computer science, ecology, economics, and sociology. The basic concept map of geographical science based on artificial intelligence provides an important knowledge bridge and enabling tool for cross-disciplinary integration. In terms of interdisciplinary knowledge integration, concept maps can achieve semantic alignment and association mining of concepts between geographical science and other disciplines, breaking down the knowledge barriers between disciplines. By correlating concepts such as "spatial distribution" and "regional differences" in geographical science with those in economics like "industrial layout" and "regional economic growth" through maps, knowledge support can be provided for regional economic geography research. In terms of the innovation of interdisciplinary research methods, the integration of concept maps and artificial intelligence technology can promote the innovation of interdisciplinary research methods. By integrating the knowledge reasoning ability of concept maps with big data analysis technology, interdisciplinary research such as "ecosystem service value assessment" and "regional sustainable development evaluation" in ecological economics is carried out to enhance the scientificity and accuracy of the research. In terms of cross-domain application expansion, the interdisciplinary integration based on geographic concept maps can give rise to new application scenarios and fields. In the construction of smart cities, by integrating geographical concept maps with knowledge from fields such as urban management, transportation, and energy, a knowledge graph for smart cities is constructed to provide intelligent support for urban traffic dispatching, optimal resource allocation, emergency management, and more. In climate change research, by integrating concepts and relationships from multiple disciplines such as geography, meteorology, and ecology, a knowledge graph for climate change impact assessment is constructed to provide a scientific basis for global climate change response. Research shows that the application of interdisciplinary integrated knowledge graphs can increase the comprehensive benefits of enterprises by 10% to 15%, with a potential market space exceeding 100 billion yuan.

5.Conclusions

This paper reviews the construction methods and application value of the basic concept map of geographical science based on artificial intelligence, clarifies its core connotation and intelligent construction requirements, deeply analyzes the key technical characteristics and application effects of multi-source data preprocessing, concept recognition and classification, dynamic relationship mining and map optimization, and explains the application value from three aspects: knowledge sorting, intelligent solution, and cross-disciplinary integration. And present the advantages of AI methods over traditional methods through quantitative tables. Research shows that AI technology effectively breaks through traditional limitations, achieving a text concept recognition accuracy rate of over 94%, graph updates within seconds, and an increase in decision response efficiency of more than 35%. At present, there are still challenges such as handling ambiguity of geographical concepts and fusing cross-modal data. In the future, it is necessary to deepen the integration of AI and geographical science theories, optimize model algorithms, expand application scenarios, and provide stronger knowledge support for the major strategic needs of relevant countries.

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