Asia Pacific Science Press

Journal of Educational Theory and Practice
ISSN(O):3005-9313
ISSN(P):3005-9305
Vol. 2 No.3 (2025)

Innovative GIS Software Application Courses for Sustainable Education: Integrating Large Language Models and AI Agents

Ge Shi[1]*, Chuang Chen[2], Chanfang Shu[1]

1.School of Geomatics Science and Technology, Nanjing Tech University, Nanjing, 211816, China

2.College of Electrical Engineering and Control Science, Nanjing Tech University, Nanjing, 211816, China

Corresponding author: Ge Shi, 202010006850@njtech.edu.cn

Abstract: With the rapid development of artificial intelligence technology, the field of education is undergoing profound changes. Geography, as a highly integrative and practical discipline, involves extensive spatial data analysis and visualization operations in its teaching process. Traditional teaching models are insufficient in meeting the personalized learning needs of students. To address this challenge and promote sustainable practices in teacher education, this study takes the course “GIS Software Application” as the foundation and integrates advanced artificial intelligence technologies, particularly large language models (LLM) and AI agents, to construct an innovative teaching system. By leveraging the powerful generative capabilities of LLM, the system generates a variety of teaching resources, such as texts, images, and videos, to enrich teaching content and cater to the diverse learning needs of students. Meanwhile, AI agents provide personalized learning path planning, real-time Q&A, and learning effect assessment services during the teaching process, thereby significantly enhancing teaching efficiency and quality. Focusing on the design of GIS software application courses based on LLM and AI agents, this study offers a practical example for the intelligent transformation of geography education. It contributes to promoting the innovative development of geography education in the era of artificial intelligence and accelerating the modernization of geography education. This approach not only enhances the educational experience but also fosters a new generation of educators equipped with sustainable practices and digital technologies.

Keywords: Large Language Models; GIS Software Application; Course Design; AI Agents; Teaching Innovation

Published: Aug 20, 2025

DOI: https://doi.org/10.62177/jetp.v2i3.532

1.Introduction

With the rapid advancement of artificial intelligence (AI) technologies, the field of education is undergoing unprecedented and profound transformations. As a core driving force of the Fourth Industrial Revolution, AI, with its superior capabilities in data processing, pattern recognition, and autonomous learning, has broken through many limitations of traditional education in terms of time and space dimensions as well as resource allocation. It has not only optimized the allocation of educational resources but also opened up entirely new possibilities for personalized learning and intelligent teaching [1-5]. In the field of Geographic Information Systems (GIS), the impact of AI is particularly remarkable. It has not only propelled GIS technology towards intelligent evolution but also brought unprecedented opportunities and challenges for GIS education innovation.

GIS, as an integrative and highly practical discipline, is widely applied in urban planning, environmental monitoring, traffic management, and other fields [6-8]. GIS software application courses involve complex spatial data analysis, cartographic tool usage, and interdisciplinary practice [9]. Traditional GIS software application course designs have long relied on fixed teaching content and standardized operational training, which have multiple limitations [10, 11]. First, the presentation of teaching resources is monotonous, primarily consisting of static texts and preset cases, which fail to cater to students' diverse cognitive styles and learning needs. Second, the course content updates lag behind the rapid development of GIS technology, with insufficient coverage of cutting-edge functions such as natural language interaction and intelligent spatial analysis. Third, the teaching process lacks a dynamic feedback mechanism. Courses often emphasize the imparting of operational skills, making it difficult for teachers to provide real-time guidance on students' individual problems during operations. This neglects students' deep understanding of data analysis, resulting in students' superficial mastery of complex GIS tools. Moreover, traditional teaching methods are usually lacking in interactivity, making it easy for students to feel bored and lose motivation during the learning process. These issues make it difficult for traditional courses to cultivate students' core competencies to address geographical issues in the intelligent era.

Large language models (LLMs) are generative AI models based on the Transformer architecture. Through pre-training on large-scale text data, they can generate human-like text, answer questions, assist with translation, and summarize information [12-16]. The Transformer employs a self-attention mechanism, enabling the model to dynamically capture long-range dependencies in text, such as weighing the importance of different words when generating sentences. In recent years, several large language models, including GPT, BERT, XLNet, T5, and RoBERTa, have emerged and been widely applied [17-18]. These models have demonstrated strong capabilities in natural language processing, such as text generation, question-answering systems, and machine translation. For instance, the GPT series of models, developed by OpenAI, use a unidirectional Transformer decoder architecture to process input sequences from left to right, predicting the next word based on the preceding context. This autoregressive generation method has led to their excellent performance in language generation [19]. From GPT-1 to GPT-4, the scale of model parameters has continuously expanded, the volume of training data has increased, and performance has significantly improved [20]. For example, GPT-3, with its massive 175 billion parameters, possesses powerful few-shot learning and context learning abilities. It can complete complex tasks such as article generation, code writing, and logical reasoning through natural language prompts. GPT-4 has introduced multimodal capabilities, supporting dual-modality input of text and images, which further broadens its application scope [21, 22]. BERT, launched by Google in 2018, employs a bidirectional Transformer encoder architecture that encodes text simultaneously in both forward and backward directions, capturing comprehensive contextual semantics and grammatical information. This results in a deeper and more accurate understanding of language [23, 24]. To enhance comprehension, BERT incorporates two tasks during pre-training: masked language modeling and next sentence prediction. In the masked language modeling task, randomly masking words in the input text and having the model predict the masked words based on context forces it to deeply understand semantic relationships between words and contextual dependencies. The next sentence prediction task, which judges the logical relationship between two sentences in a text, enables BERT to learn the coherence and semantic associations between sentences. This is beneficial for handling tasks such as question-answering systems and text summarization that require an understanding of long-text logic [25, 26].

With the evolution of technology, researchers have proposed various improvement methods, such as model merging and multimodal learning, to further enhance model performance and application scope. The breakthrough development of large language models (LLMs) has provided innovative solutions for the reform of GIS software application courses. By integrating natural language processing, knowledge graphs, and multimodal generation technologies, LLMs can transform complex GIS operation commands into natural language interactions, significantly reducing the learning threshold. Moreover, pre-trained models based on vast amounts of geographic data and knowledge can dynamically generate personalized learning resources to meet differentiated teaching needs [27]. Additionally, the intelligent dialogue and real-time feedback mechanisms of LLMs can create a "human-computer collaborative" teaching environment, assisting students in completing the entire process of spatial data processing and intelligent decision-making training. This deep integration not only revolutionizes the modes and methods of GIS teaching but also lays the foundation for cultivating compound geographic information talents with AI thinking [28].

In summary, this study explores the design pathways of GIS software application courses through large language models, leveraging the advantages of AI to overcome the shortcomings of traditional course design. It constructs an AI agent for the "GIS Software Application" course. The system aims to provide personalized learning paths for students of this course, dynamically adjust teaching content based on student abilities, and offer immediate feedback and assessment. It is intended to promote the intelligent and personalized development of geography education. This study seeks to provide new ideas for the reform of geography teaching and offer theoretical and practical references for the intelligent transformation of geography education.

2.Course framework design

2.1 Course content and objective

Traditional "GIS Software Application" courses center on the theory of Geographic Information Systems and practical software operation, covering data management, spatial analysis, visualization, and industry applications to form a comprehensive system from basic to advanced applications [29]. The course begins with foundational theories, including spatial data models (vector, raster, topological relationships), coordinate system transformations (such as WGS84 and UTM projections), and data collection methods (remote sensing image processing, GPS data import), establishing students' understanding of geographic information logic. It then focuses on software operation and data analysis skills, relying on mainstream platforms like ArcGIS and QGIS to train core competencies in data preprocessing (format conversion, topological error correction), spatial analysis (vector overlay, raster calculation, spatial statistics), and thematic map design (symbolization rules, 3D terrain rendering). Finally, it strengthens comprehensive abilities through industry-specific practices, such as land suitability evaluation in urban planning, flood simulation in environmental science, and emergency route optimization in public safety, incorporating interdisciplinary expansions like Python scripting (ArcPy/PyQGIS) and spatial databases (PostGIS).

In traditional course instruction, teachers are the center of teaching activities, students are recipients of knowledge, textbooks are the main content of teaching, and grades are the manifestation of teaching quality [30]. Despite the strong systematic nature of traditional courses, issues such as static case studies and delayed feedback persist. The emerging LLM-integrated teaching model compensates for the flexibility shortcomings of the traditional framework through dynamic data generation, real-time operational diagnosis, and ethical deliberation segments. Therefore, this study constructs an AI agent whose core objective is to address the pain points in traditional "GIS Software Application" course instruction through artificial intelligence technology, including abstract and difficult-to-understand knowledge points, monotonous teaching resources, insufficient teacher-student interaction, and lack of personalized learning support, to achieve the intelligent of the "GIS Software Application" course.

The "GIS Software Application" course, integrated with the AI agent, has achieved significant changes in both teaching content and form. In terms of teaching content, an LLM-empowered four-dimensional teaching framework has been formed, realizing the shift from traditional knowledge transmission to intelligent interactive teaching [31]. For example, in the data preprocessing stage, the LLM acts as an intelligent assistant, capable of automatically parsing and converting students' data processing requests in natural language (such as "extract forest areas with an elevation higher than 500 meters within a certain region") into executable GIS spatial analysis commands. Meanwhile, the LLM supports multi-turn dialog interactions to diagnose and correct topological errors in spatial data in real-time (such as unclosed line features and overlapping surface features), achieving a paradigm shift in knowledge acquisition and problem-solving. Traditional GIS knowledge bases primarily consist of static documents, whereas AI agents, combined with domain-tuned models (such as GeoGPT) and multimodal retrieval, support the decomposition of complex questions (for example, "How to assess the impact of typhoon tracks on urban transportation?" → broken down into buffer analysis, network vulnerability assessment, etc.) and provide richer learning resources in terms of interdisciplinary knowledge association (when answering "Kriging interpolation," simultaneously recommending soil pollution cases in environmental science and epidemic diffusion models in public health).

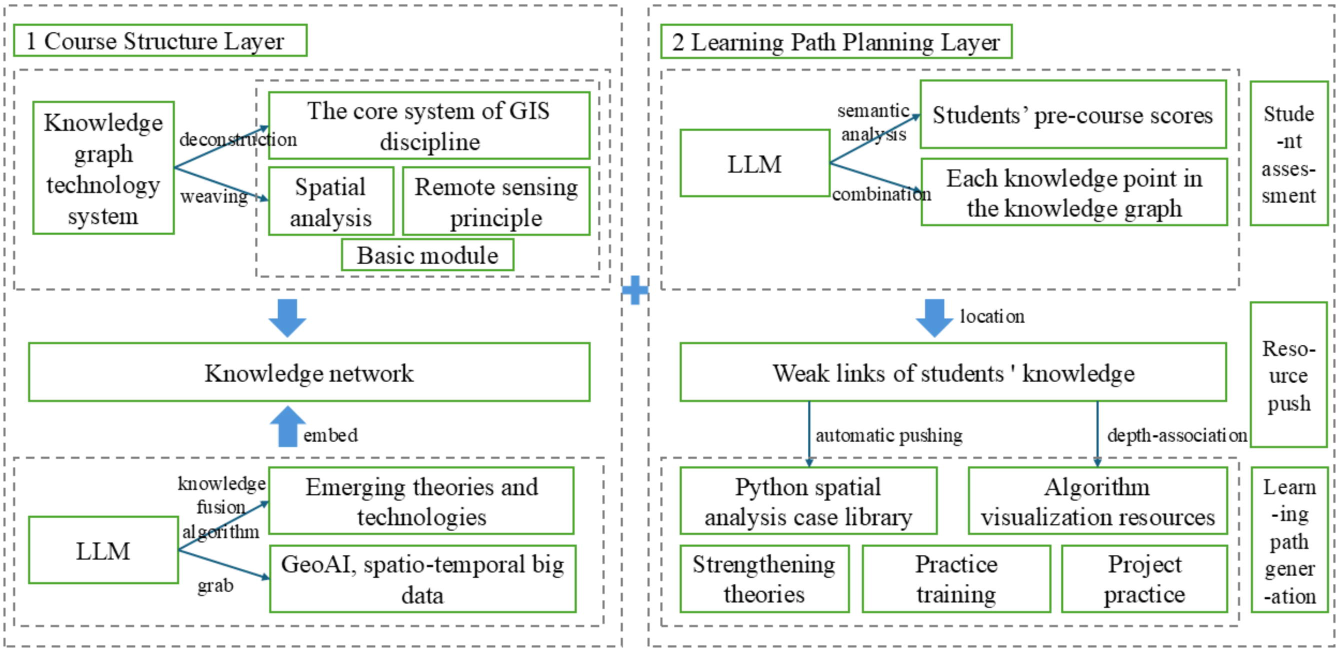
In terms of teaching form, the deep integration of the AI agent has broken the traditional one-way teaching model and constructed a new type of teaching ecosystem integrating "resource generation - interactive learning - adaptive assessment."

Relying on the powerful content generation capability of the LLM, course resources have achieved automated and personalized iteration. The system can automatically generate GIS course cases covering multiple scenarios such as urban green space planning and watershed ecological assessment according to teaching progress, industry hotspots, and students' knowledge weak points [32]. It also synchronously outputs experimental guidance documents containing data preprocessing steps, analysis tool invocation methods, and key points for result interpretation. Through generative visualization explanations, complex spatial analysis principles are transformed into intuitive teaching resources such as dynamic diagrams and 3D models.

2.2. Restructuring of the course system

The AI agent has restructured the framework of the "GIS Software Application" course, establishing a dual-driven model of "dynamic evolution of knowledge networks—intelligent adaptation of learning paths" and creating a modular and scalable teaching system (Figure 1). At the course structure level, the core knowledge system of the GIS discipline has been systematically deconstructed using knowledge graph technology. Basic modules such as spatial analysis and remote sensing principles have been woven into a hierarchical knowledge network. The LLM captures cutting-edge dynamics in the field, such as GeoAI and spatiotemporal big data analysis, in real-time. It then uses knowledge fusion algorithms to automatically embed emerging theories and technologies into the existing knowledge network, generating a course topology that includes interdisciplinary nodes such as computer science and artificial intelligence. This approach enables continuous iteration and updating of teaching content.

Figure 1. Structure of course system



In terms of learning path planning, the AI agent semantically analyzes students' previous course grades using the LLM and, in combination with the association weights of each knowledge point in the knowledge graph, accurately identifies students' weak areas of knowledge. For students lacking spatial statistical skills, the system not only automatically pushes the Python spatial analysis case library but also deeply links algorithm visualization resources, generating personalized learning paths that cover theoretical reinforcement, practical training, and project practice. This process promotes the transformation of the course from a linear, standardized teaching model to a dynamic, adaptive, and precise intelligent system.

3.AI Agent architecture

3.1 Functional modules

The functional modules of the AI agent primarily consist of two core components: LLM-empowered GIS foundational theory learning and interactive experimentation and project development. The GIS foundational theory learning module aims to help students grasp the core concepts, principles, and methods of GIS. Leveraging the powerful semantic understanding and knowledge integration capabilities of the LLM, this module provides personalized learning paths for students through natural language interaction. The interactive experimentation and project development module, on the other hand, is practice-oriented and relies on the LLM's code generation and logical deduction capabilities to break down the technical barriers of traditional experimental operations.

These two modules are not independent but are deeply integrated through data sharing and intelligent linkage. Specifically, the foundational theory learning module continuously records students' mastery of GIS spatial analysis, data modeling, and other knowledge during the teaching process. These records serve as crucial references in the interactive experimentation and project development phase, where practice tasks are matched to students' knowledge reserves. For instance, if the system detects that a student has a weak grasp of spatial interpolation algorithms, it will prioritize sending experimental projects with lower data processing difficulty aimed at consolidating the application of these algorithms, ensuring that the practice difficulty is appropriate to the student's ability. Meanwhile, the interactive experimentation and project development module continuously "feeds back" to the foundational theory learning. Problems encountered by students in practical operations, whether data format conversion issues in ArcGIS platform's network analysis or logical errors in spatial analysis script writing in the Python environment, are all transmitted in real-time to the foundational theory learning module. The LLM then dynamically optimizes the teaching content based on this feedback, either by deepening the explanation of relevant knowledge points or by adjusting the presentation of teaching cases, creating a virtuous cycle where "theory guides practice and practice feeds back into theory." This two-way interactive mechanism runs throughout the student's learning process, acting like a bridge connecting theory and practice. As students explore and make mistakes, they gradually deepen their understanding of the GIS technology system, moving from simply memorizing the principles of geographic information systems to skillfully applying them to solve real-world problems such as urban planning site selection and ecological environment monitoring. This innovative learning model propels GIS education from the traditional one-way didactic teaching to a new paradigm of intelligent education centered on students and focused on capability cultivation.

3.1.1 LLM-empowered GIS Foundational Theory Learning

In the GIS foundational theory learning module, the AI agent constructs a natural language interaction interface based on GPT-4, enabling dynamic parsing and cross-modal output of GIS concepts. Whether it is spatial data structures, geographic coding, spatial analysis algorithms, or the principles of map projection, the LLM can transform these complex concepts into vivid and understandable examples and explanations. Students need only to ask simple questions to receive customized knowledge graph organization and difficulty analysis.

The module also features intelligent diagnostic capabilities. By analyzing students' questions and answers during the learning process, it assesses their knowledge acquisition in real-time and provides targeted supplementary learning materials and extended reading content, forming a closed-loop learning system of "learning - feedback - reinforcement." For instance, when a student asks about the principles of spatial interpolation algorithms, the system not only generates textual explanations (such as the differences between Kriging and inverse distance weighting) but also outputs visual flowcharts for meteorological data interpolation and Python code snippets (including ArcPy interface call examples), creating a three-dimensional cognitive support of "theory - illustration - practice."

Furthermore, leveraging the semantic analysis capabilities of the BERT model, the system extracts knowledge from GIS textbooks and academic literature to build a knowledge graph network covering 12 core areas, including spatial analysis and geographic modeling. Through knowledge association algorithms, the system can automatically identify the relevance of "Kriging" to application scenarios such as meteorological prediction and soil sampling, and push typical cases and cutting-edge research results with a match rate of over 85%, expanding students' theoretical cognitive boundaries.

3.1.2 Interactive Experimentation and Project Development

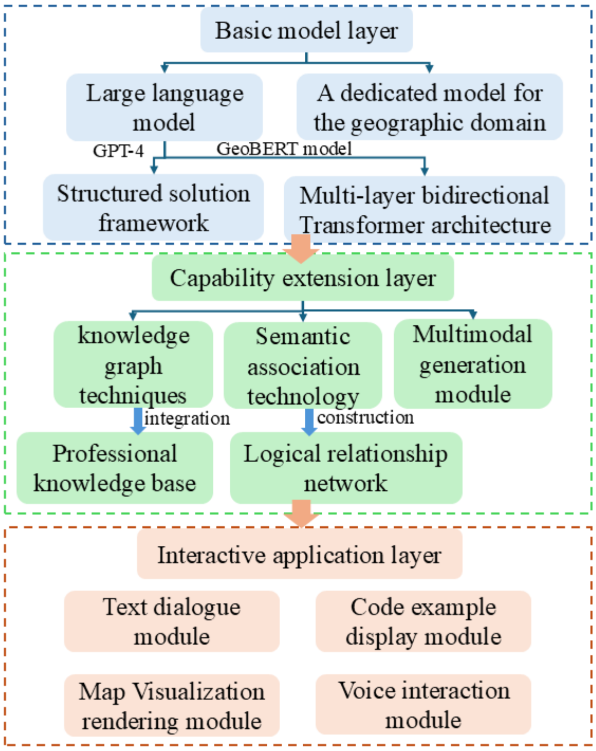
In the interactive experimentation and project development module, the AI agent constructs a real-time monitoring system of "perception - analysis - feedback." By employing computer vision technology to capture the ArcGIS operation interface in real-time and combining natural language processing algorithms to parse experimental logs, the system can accurately identify common issues such as parameter configuration errors and logical flaws in the analysis process. It then swiftly generates feedback reports containing error localization, correction steps, and demonstration videos of operations. For group practice projects, the AI agent participates in scheme design as a virtual team member. Based on an industry knowledge base and a repository of best practice cases, it uses semantic matching algorithms to recommend optimized technical routes. For instance, in a "urban traffic simulation" project, the system can automatically suggest data cleaning plans for OpenStreetMap road networks, parameter setting guidelines for SUMO traffic simulation, and Echarts visualization templates. This guidance helps students transform theoretical knowledge into practical solutions, achieving a coordinated enhancement of GIS theoretical understanding and practical skills.

Within this module, students can also propose experimental requirements, such as "conducting congestion hotspot analysis using GIS based on urban traffic flow data." The LLM can rapidly generate code frameworks corresponding to platforms like Python and ArcGIS. It provides step-by-step guidance in conjunction with data preprocessing, algorithm invocation, and visualization presentation. During the project development phase, from requirement analysis, data collection, model construction to result presentation, the AI agent can participate throughout. It assists students in optimizing scheme design and resolving technical challenges encountered in development, such as spatial data compatibility issues and difficulties in selecting analysis models.

3.2 System architecture

The AI agent employs a layered architectural design, with its core structure comprising three main layers: the foundational model layer, the capability expansion layer, and the interactive application layer (Figure 2). The foundational model layer is primarily responsible for the underlying data processing and core algorithm support, acting as the "foundation" of the entire AI agent. It handles the cleaning, storage, and management of vast amounts of geospatial data and the GIS theoretical knowledge base [33]. The capability expansion layer, built upon the foundational model layer, serves as the "function expansion library" of the AI agent. Through modular design, it enables flexible combination and expansion of functionalities. The interactive application layer functions as the "dialogue window" between users and the AI agent, transforming complex GIS technologies and analysis results into intuitive and user-friendly interfaces.

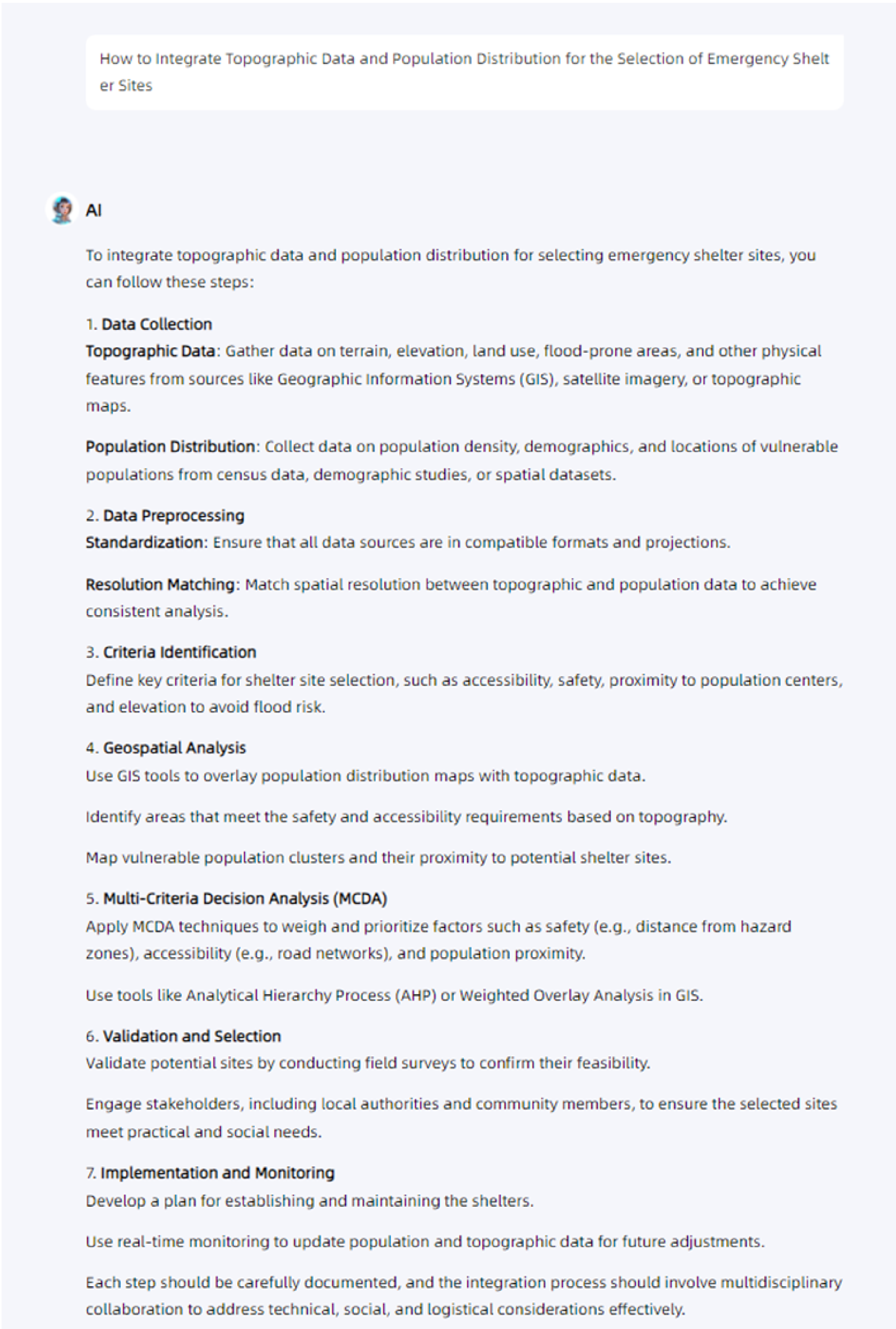
Figure 2. System architecture of the AI Agent



3.2.1 Foundational model layer

In the foundational model layer, the system employs a hybrid architecture combining general-purpose large language models with domain-specific models for geography. GPT-4 serves as the core reasoning engine, handling complex semantic understanding and knowledge generation tasks [34]. Leveraging its robust capabilities for multi-turn dialogue comprehension, complex logical reasoning, and knowledge generation, GPT-4 efficiently processes complex semantic structures in natural language queries. For instance, it can parse compound questions such as "How to select emergency shelters by integrating topographic data and population distribution" and generate structured answer frameworks (Figure 3).

Figure 3. AI agent assistant answer



How to Integrate Topographic Data and Population Distribution for the Selection of Emergency Shelter Sites

AI

To integrate topographic data and population distribution for selecting emergency shelter sites, you can follow these steps:

1. **Data Collection**

Topographic Data: Gather data on terrain, elevation, land use, flood-prone areas, and other physical features from sources like Geographic Information Systems (GIS), satellite imagery, or topographic maps.

Population Distribution: Collect data on population density, demographics, and locations of vulnerable populations from census data, demographic studies, or spatial datasets.

2. **Data Preprocessing**

Standardization: Ensure that all data sources are in compatible formats and projections.

Resolution Matching: Match spatial resolution between topographic and population data to achieve consistent analysis.

3. **Criteria Identification**

Define key criteria for shelter site selection, such as accessibility, safety, proximity to population centers, and elevation to avoid flood risk.

4. **Geospatial Analysis**

Use GIS tools to overlay population distribution maps with topographic data.

Identify areas that meet the safety and accessibility requirements based on topography.

Map vulnerable population clusters and their proximity to potential shelter sites.

5. **Multi-Criteria Decision Analysis (MCDA)**

Apply MCDA techniques to weigh and prioritize factors such as safety (e.g., distance from hazard zones), accessibility (e.g., road networks), and population proximity.

Use tools like Analytical Hierarchy Process (AHP) or Weighted Overlay Analysis in GIS.

6. **Validation and Selection**

Validate potential sites by conducting field surveys to confirm their feasibility.

Engage stakeholders, including local authorities and community members, to ensure the selected sites meet practical and social needs.

7. **Implementation and Monitoring**

Develop a plan for establishing and maintaining the shelters.

Use real-time monitoring to update population and topographic data for future adjustments.

Each step should be carefully documented, and the integration process should involve multidisciplinary collaboration to address technical, social, and logistical considerations effectively.

To address the knowledge gaps of general-purpose models in the GIS domain, the system incorporates the GeoBERT model, which is trained on a geography-specific text corpus. This corpus integrates professional resources such as ArcGIS official technical documents, SCI/EI geographical academic papers, and natural resources industry reports. The GeoBERT model employs a multi-layer bidirectional Transformer architecture for feature extraction and semantic encoding. Specifically tailored for GIS-related tasks, the GeoBERT model has been fine-tuned for spatial relationship reasoning (e.g., topological judgment, buffer calculation logic), specialized term interpretation (e.g., “UTM projection coordinate system conversion rules”), and geographical entity recognition (e.g., place names, geographical feature classification).

GeoBERT is a pre-trained language model specifically designed for Chinese address texts [35]. Through a multi-task joint training mechanism, it captures spatial semantic relationships and administrative hierarchy features in address data. Based on the traditional BERT architecture, GeoBERT has been improved to effectively address address text processing issues in geographic information systems.

3.2.2 Capability expansion layer

In the capability expansion layer, the system employs knowledge graph technology to deeply deconstruct and reconstruct the knowledge system of the GIS discipline. Through techniques such as knowledge extraction, relationship mining, and ontology construction, the system systematically organizes and integrates professional knowledge from 12 core areas, including spatial analysis, geographic modeling, remote sensing image processing, and cartography, constructing a professional knowledge base containing over 5000 knowledge points and more than 20000 relationship edges [36]. This knowledge base not only enables the structured storage of GIS foundational theories, software operation methods, and industry application cases but also establishes a logical relationship network between knowledge points through semantic association technology, supporting rapid retrieval and reasoning of complex knowledge.

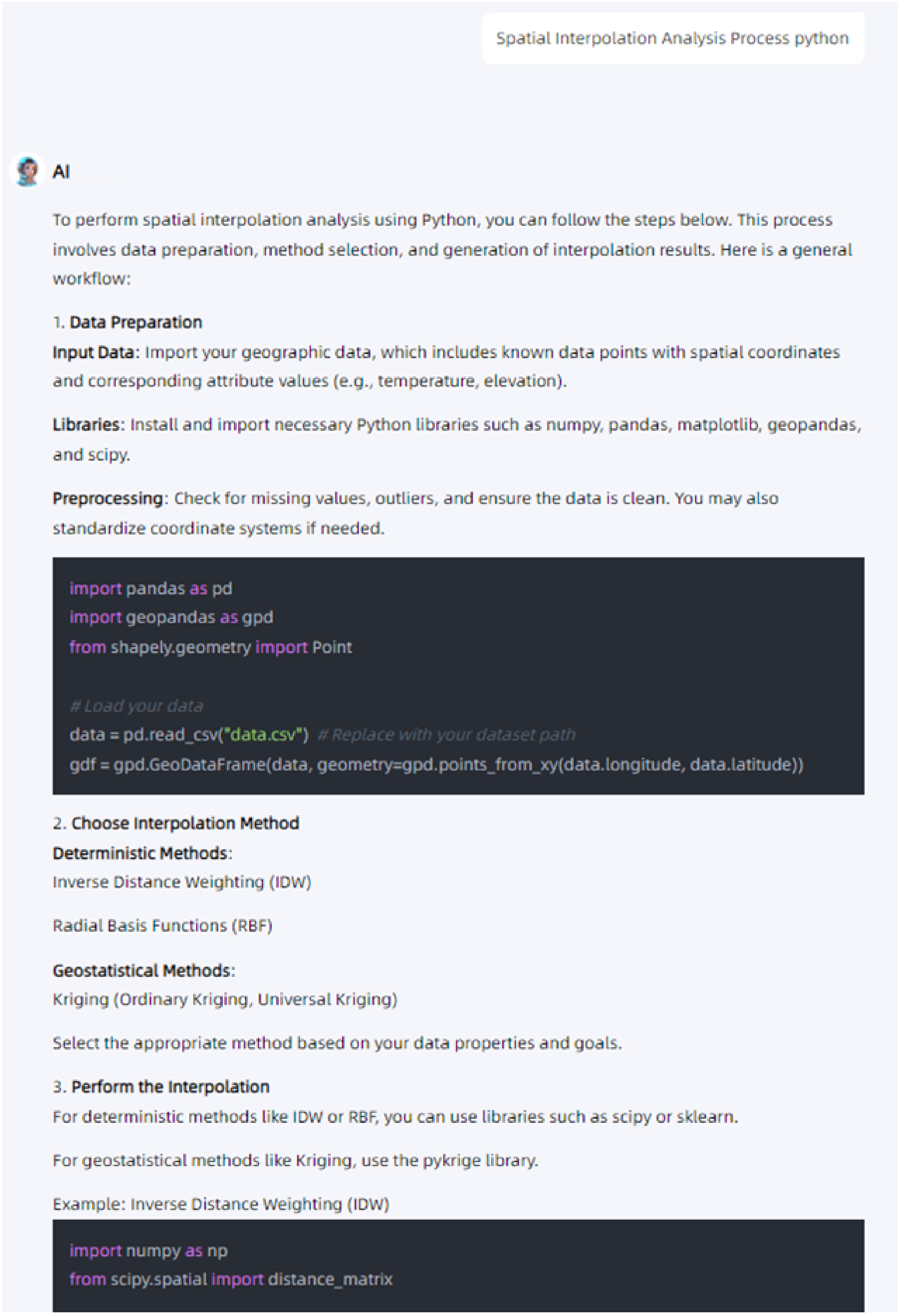
Additionally, the system has developed a multimodal generation module. Based on natural language processing and computer graphics technology, this module automatically transforms the textual content output from the foundational model layer into diverse forms such as Python code snippets, ArcGIS operation scripts, spatial analysis flowcharts, and 3D visualization models [37]. For example, when the system outputs a textual description of the “spatial interpolation analysis process,” the multimodal generation module can simultaneously generate the corresponding Python implementation code, screenshots of ArcGIS tool operation steps, and 3D visualization maps displaying the interpolation results (Figure 4). These diverse forms cater to the needs of students with different learning styles, significantly enhancing the efficiency and effectiveness of knowledge transfer.

In the capability expansion layer, the AI agent not only provides detailed answers to specific questions but also recommends related knowledge points based on the content of the question, helping students to further expand and deepen their understanding (Figure 5). The relationship between the recommended knowledge points and the questioned knowledge points can be parallel, progressive, or supplementary. For example, after answering a question about spatial interpolation analysis, the AI agent will recommend related knowledge points such as “Fundamentals of Spatial Analysis,” “Geostatistics,” and “Data Interpolation Methods in GIS.” These knowledge points are displayed in the form of a knowledge graph, clearly showing their logical relationships. In this way, the AI agent not only answers the student’s question but also provides more learning suggestions, guiding students to explore and learn more deeply.

Specifically, the AI agent follows the following steps to provide related knowledge point recommendations after answering a question:

Knowledge Point Association Analysis: The AI agent uses knowledge graph technology to analyze the relationships between the questioned knowledge point and other knowledge points. These relationships include parallel relationships (such as “spatial interpolation analysis” and “fundamentals of spatial analysis”), progressive relationships (such as “spatial interpolation analysis” and “geostatistics”), and supplementary relationships (such as “spatial interpolation analysis” and “data interpolation methods in GIS”). Through semantic analysis and relationship mining algorithms, the AI agent can identify the most relevant core knowledge points related to the questioned knowledge point and rank them according to their importance and relevance.

Figure 4. AI agent assistant with python code



Personalized Recommendations: Based on the student's knowledge reserves and learning progress, the AI agent generates a personalized list of knowledge point recommendations for each student. The recommendation list not only includes knowledge points directly related to the questioned knowledge point but may also include some extended knowledge points to help students build a more comprehensive knowledge system. For example, after answering the question "spatial interpolation analysis process," the AI agent will recommend the following knowledge points:

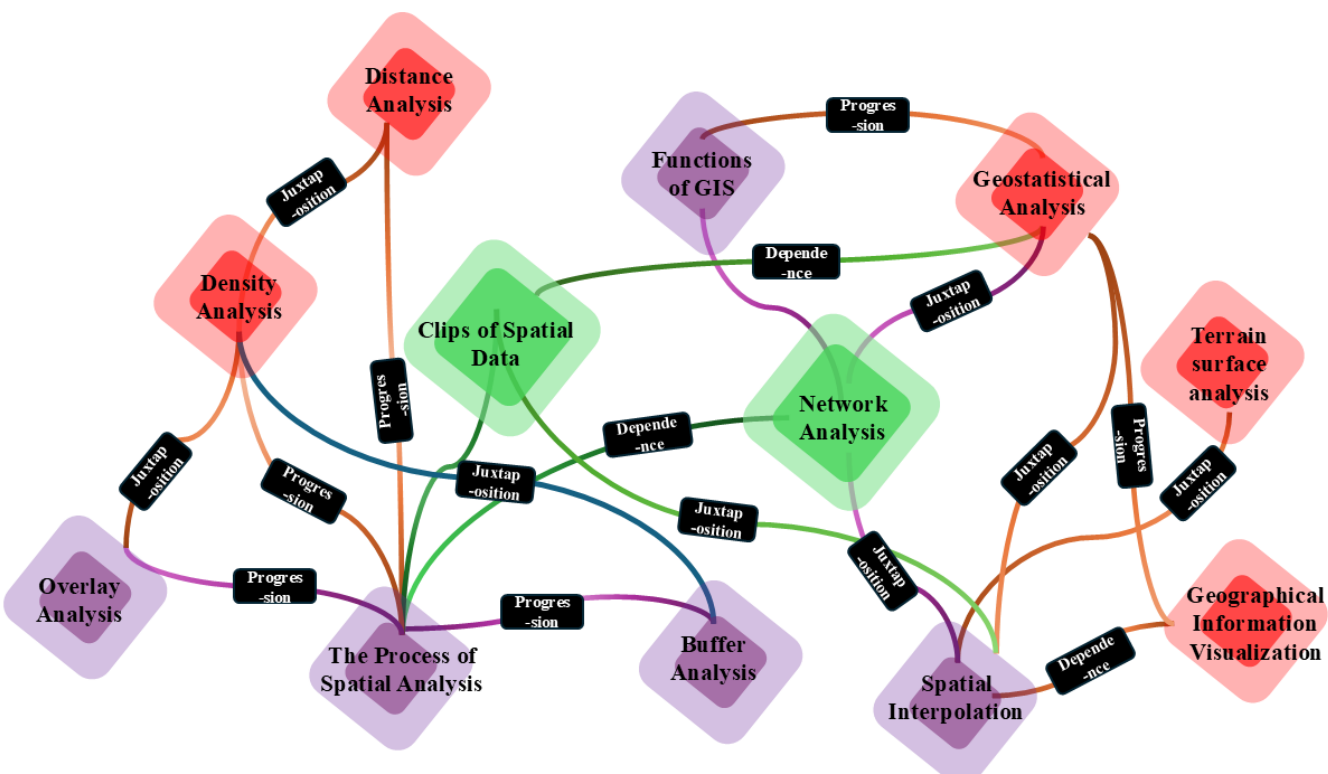
Parallel Relationship: Fundamentals of Spatial Analysis, Geographic Data Visualization

Progressive Relationship: Geostatistics, Spatial Data Modeling

Supplementary Relationship: Data Interpolation Methods in GIS, Spatial Data Quality Assessment

Knowledge Graph Visualization: The AI agent displays the recommended knowledge points in the form of a knowledge graph. The knowledge graph clearly shows the logical relationships between knowledge points through nodes and edges [38]. Each node represents a knowledge point, and the edges represent the relationships between knowledge points (such as parallel, progressive, supplementary). For example, the knowledge graph can show the parallel relationship between the "spatial interpolation analysis" node and the "fundamentals of spatial analysis" node, as well as the progressive relationship with the "geostatistics" node. Through this visualization method, students can intuitively understand the connections between knowledge points, thereby better constructing a knowledge network.

Figure 5. AI agent assistant with knowledge recommendation



Learning Path Planning: Based on the recommended knowledge points, the AI agent plans a personalized learning path for students. The learning path includes the recommended learning order, learning resources (such as textbooks, cases, videos, etc.), and assessment methods (such as quizzes, projects, etc.). For example, the AI agent may suggest that students first review the "fundamentals of spatial analysis," then learn "geostatistics," and finally delve into "data interpolation methods in GIS." Each knowledge point's learning path includes specific resources and assessment methods to ensure that students can systematically master the relevant knowledge.

Through these steps, the AI agent not only answers the student's question but also provides more learning suggestions to help students build a more comprehensive knowledge system and guide them to explore and learn more deeply. This personalized and systematic learning support significantly improves students' learning efficiency and effectiveness.

3.2.3 Interactive application layer

The interactive application layer adopts a multimodal interaction design concept, supporting students in acquiring GIS knowledge through various means such as natural language questions and voice commands. The system provides feedback in multimodal forms, including textual and graphical reports, dynamic maps, and voice explanations, creating an efficient human-computer interactive learning environment. This layer integrates four core functional modules:

Textual Dialogue Module: Real-time interaction is enabled through a Web interface.

Code Example Display Module: It offers online editing, syntax checking, and one-click execution for ArcPy scripts, with

JupyterNotebook kernel embedded for step-by-step code debugging.

Map Visualization Rendering Module: It supports dynamic display of 2D thematic maps and 3D terrain scenes, allowing users to explore spatial data through mouse dragging and zooming operations.

Voice Interaction Module: It supports bilingual (Chinese and English) voice input and output, with acoustic model optimization for GIS-specific terminology.

The system supports multi-channel input modes. Students can pose complex questions in natural language (e.g., “How to analyze the urban heat island effect using GIS”) and quickly access specific functions through voice commands (e.g., “Open the buffer analysis tool”). On the output side, the system employs an adaptive multimodal feedback strategy: for theoretical questions, it generates structured reports with rich text and graphics, expanding related knowledge through knowledge graphs; for practical needs, it synchronously presents dynamic map operation demonstrations, code execution results, and visual analysis outcomes; for complex process explanations, it activates voice-guided tours, complemented by highlighted map elements and code comments, to achieve an integrated learning experience of “listening, watching, and practicing.” This multimodal interaction mechanism effectively lowers the learning threshold for GIS knowledge and significantly enhances the efficiency of human-computer interaction and learning immersion.

4.Discussion

This study successfully integrated an AI agent with GIS software application courses, leveraging large language models (LLM) to validate the innovative potential of artificial intelligence in the field of geographic information science education. The intelligent generation of multimodal resources has broken the bottleneck of traditional GIS teaching resources, which were characterized by their singular form and slow updates, while the AI knowledge graph has significantly enhanced the richness and timeliness of teaching content. The AI agent has effectively covered the entire teaching process, facilitating a shift in student learning from passive reception to active exploration. In the foundational theory learning of GIS, students are no longer confined to the fixed knowledge framework of traditional textbooks. Relying on the knowledge integration capabilities of LLM, the AI agent generates personalized learning materials that include cutting-edge research trends and industry application cases based on students’ knowledge reserves and learning progress. In practical operation segments, the AI agent acts as a “virtual tutor,” providing students with real-time, precise guidance. When encountering difficulties in data processing and model construction during complex GIS software operations and experimental projects, students can query the agent through the interactive application layer at any time. Based on its built-in knowledge graph and algorithm library, the agent swiftly identifies the root of the problem and offers solutions in the form of step-by-step breakdowns, code examples, and error prompts.

Despite achieving phased results, the AI agent designed for GIS courses still faces multiple challenges. First, the accuracy and reliability of model outputs are limited. When dealing with complex GIS professional issues, LLM may generate logically flawed or outdated conclusions due to the lack of in-depth domain knowledge calibration. For instance, in scenarios involving high-precision spatial data calculations or emerging GIS technology applications, the professional adequacy of model outputs is insufficient, necessitating secondary human verification and correction. Second, educational ethics and data security risks are becoming increasingly prominent. LLM training relies on large-scale data, and the privacy protection of teaching data from teachers and students in course practice, the copyright ownership of model-generated content, and potential algorithmic bias issues all require the establishment of comprehensive regulatory mechanisms [39]. Third, the human-computer collaborative model is not yet mature. Teachers and students, when utilizing intelligent tools, are prone to over-reliance on technology at the expense of independent thinking. How to balance AI assistance with human educational subjectivity still requires further exploration. Additionally, in terms of system performance, domain-tuned models (such as GeoGPT) lack sufficient semantic understanding of geospatial data, especially when handling complex spatial relationship reasoning tasks, resulting in logical deviations and ambiguous result interpretations; during multi-turn dialog interactions, long text inputs easily lead to context memory decay in the model, affecting the accuracy of data processing instruction parsing [40]. From an educational practice perspective, course resources generated based on LLM face the risk of content homogenization, failing to fully cover the long-tail demands of GIS teaching, and over-reliance on AI-generated content may weaken students’ independent thinking and knowledge construction abilities. Moreover, AI agents face data privacy and ethical risks, with student behavior data collected during teaching posing leakage risks, and the reliability and authority of model-generated content still requiring human verification, making fully automated teaching unattainable. In terms of technical deployment, the system demands substantial hardware computing resources, and the cost of computational power required for model training and real-time response restricts its large-scale promotion and application [41].

Future research can break through in three areas: First, optimize the domain adaptation of LLM. By leveraging GIS-specific knowledge graphs and fine-tuning with small datasets, enhance the model's professionalism in scenarios such as geospatial analysis and spatial decision support, and establish a dynamic optimization mechanism for domain model training [42]. Continuously collect real problem data from teaching practices and dynamically adjust model parameters using reinforcement learning algorithms to improve the accuracy of geographical semantic understanding and task processing. Second, explore in-depth human-computer collaborative teaching models. Design teaching segments that guide students to verify AI suggestions and independently optimize analysis processes, balancing technological assistance with autonomous learning [43]. Finally, perfect the security and ethical framework of intelligent teaching systems. Establish data encryption and anonymization standards, develop AI content credibility assessment tools, and promote collaborative norm development among educational institutions, businesses, and policymakers [44]. Additionally, strengthen research on integrating LLM with real-time GIS data interfaces and IoT devices to align course content with cutting-edge application scenarios such as smart cities and disaster early warning, thereby further enhancing the practical value and contemporary relevance of GIS education.

5.Conclusions

Guided by the transformation of education through digitalization, this study addresses long-standing issues in the "GIS Software Application" course, such as fragmented resources, abstract cognition, and singular assessment, by constructing an AI agent based on large language models (LLM). The deep integration of the AI agent has brought revolutionary changes to the course, achieving significant breakthroughs in both teaching content and course format.

In terms of teaching content, the LLM-empowered four-dimensional teaching framework has restructured the mode of knowledge transmission and acquisition. It transitions from intelligent interaction in data preprocessing to the decomposition and resolution of complex problems and shifts from learning within a single domain to interdisciplinary knowledge association. This framework effectively propels GIS teaching from traditional rote instruction to interactive learning. Through dynamic data generation and real-time operational diagnosis, the AI agent not only enhances the efficiency of knowledge acquisition but also strengthens students' understanding and application of complex GIS concepts.

Regarding course format, the new teaching ecosystem of "resource generation - interactive learning - adaptive assessment" breaks the limitations of time and space, achieving dynamic updates and personalized adaptation of course resources. The system automatically generates GIS course cases covering multiple scenarios based on teaching progress, industry hotspots, and students' knowledge weaknesses. It also transforms complex spatial analysis principles into intuitive teaching resources through generative visualization explanations. This new teaching ecosystem significantly improves the relevance and timeliness of teaching resources, greatly enhancing student engagement and teaching effectiveness.

The system not only improves students' mastery of GIS theory and practical knowledge but also cultivates their ability to analyze complex problems and apply interdisciplinary knowledge. With real-time feedback and personalized guidance from the AI agent, students can continuously optimize their learning paths in practice, gradually enhancing their ability to solve practical problems.

Future research can further explore the in-depth integration of AI agents with GIS professional software, optimize the accuracy of domain models, and strengthen long-term tracking and evaluation of intelligent teaching effects. Additionally, it is necessary to perfect the security and ethical framework of intelligent teaching systems, establish data encryption and anonymization standards, and develop AI content credibility assessment tools to continuously advance GIS education in a smarter and more efficient direction. Through these efforts, we aim to further enhance the quality and effectiveness of GIS education and cultivate more high-quality talents with innovative and practical abilities in the field of geographic information science.

Funding

This research was funded by the 2024 Philosophy and Social Science Research in Colleges and Universities Program in Jiangsu Province (No. 2024SJYB0167); The Teaching Reform Project of Nanjing Tech University (No.20230077, 20250093, 20250030, 20230046); The 2025 Nanjing Tech University, General Education Course on Artificial Intelligence Curriculum Reform Project: “Intelligent Spatial Analysis”; The 2024 Nanjing Tech University, Undergraduate Course Ideological and Political Demonstration Course Construction Project: “Engineering Drawing and BIM” (No.20240008), “Environment for Intelligent Building” (No.20240001); Jiangsu Province Higher Education Teaching Reform Research Project (No. 2025JGYB346) .

Conflict of Interests

The authors declare that there is no conflict of interest regarding the publication of this paper.

Reference

[1] V, Johanna; M T, Ahmed; O, Nuno. Artificial Intelligence in K-12 Education: Eliciting and Reflecting on Swedish Teachers' Understanding of AI and Its Implications for Teaching & Learning. Education and Information Technologies, 2023, 29(4): 4085-4105.

[2] Ramteja, S.; Yusuf, S.; David, C. Platform-independent and Curriculum-oriented Intelligent Assistant for Higher Education. International Journal of Educational Technology in Higher Education, 2023, 20(1).

[3] Sajja, R.; Sermet, Y.; Cikmaz, M. Artificial Intelligence-Enabled Intelligent Assistant for Personalized and Adaptive Learning in Higher Education. Information, 2024, 15(10): 596.

[4] Knobloch, J.; Kaltenbach, J.; Bruegge, B. Increasing Student Engagement in Higher Education Using a Context-Aware Q&A Teaching Framework. Technical University of Munich, Munich, Germany. Technical University of Munich, Munich, Germany; Technical University of Munich, Munich, Germany, 2018.

[5] Beaver, I.; Mueen, A. On the Care and Feeding of Virtual Assistants: Automating Conversation Review with AI. AI Magazine, 2021, 42(4): 29-42.

[6] Li, H. F. Context Optimization Strategy of Multimedia Technology in Geography Teaching: Review of Classic Cases of GIS-Assisted Geography Teaching. China Science and Technology Papers, 2020, 15(03): 382-383.

[7] Bo, Z. Humanistic GIS: Toward a Research Agenda. Annals of the American Association of Geographers, 2022, 112(6): 1576-1592.

[8] Luke, B.; Nick, L. For Geographical Imagination Systems. Annals of the American Association of Geographers, 2021, 111(1): 26-35.

[9] Zong, W.; Lin, W. P. Exploration on Curriculum Ideology and Politics Teaching: GIS Software and Applications from the Perspective of Ecological Civilization Construction. Journal of Nanjing Normal University (Natural Science Edition), 2021, 44(S1): 19-24.

[10] Reicher, H.; Frenkel, Y.; Lavi, J. M. A Generative AI-Empowered Digital Tutor for Higher Education Courses. Information, 2025, 16(4): 264.

[11] Ciolli, M.; Federici, B.; Ferrando, I. FOSS Tools and Applications for Education in Geospatial Sciences. ISPRS International Journal of Geo-Information, 2017, 6(7): 225.

[12] Razvan, A.; R S, K.; James, F. Large Language Models and the Perils of Their Hallucinations. Critical Care (London, England), 2023, 27(1): 120.

[13] Huang, L.; Xue, J.; Wang, Y. Strengthening LLM Ecosystem Security: Preventing Mobile Malware From Manipulating LLM-Based Applications. Information Sciences, 2024, 681: 120923.

[14] Salim, S. M.; Hossain, I. S.; Jalal, T. LLM-Based QA Chatbot Builder: A Generative AI-Based Chatbot Builder for Question Answering. Software X, 2025, 29: 102029.

[15] Liu, J.; Tian, X.; Tong, H. Enhancing Chinese Abbreviation Prediction With LLM Generation and Contrastive Evaluation. Information Processing and Management, 2024, 61(4): 103768.

[16] Mirzaei, T.; Amini, L.; Esmaeilzadeh, P. Clinician Voices on Ethics of LLM Integration in Healthcare: A Thematic Analysis of Ethical Concerns and Implications. BMC Medical Informatics and Decision Making, 2024, 24(1): 250.

[17] Hyunsu, L. The Rise of ChatGPT: Exploring Its Potential in Medical Education. Anatomical Sciences Education, 2023, 17(5): 926-931.

[18] Horiuchi, D.; Tatekawa, H.; Oura, T. Comparing the Diagnostic Performance of GPT-4-Based ChatGPT, GPT-4V-Based ChatGPT, and Radiologists in Challenging Neuroradiology Cases. Clinical Neuroradiology, 2024, 34(4): 779-787.

[19] Zhang, Z.; Wen, L.; Jiang, Y. Evaluate Chat-GPT's Programming Capability in Swift Through Real University Exam Questions. Software: Practice and Experience, 2024, 54(11): 2129-2143.

[20] Xu, D.; Ding, L.; Zhou, Y. GPT-ZSS: A Unified Zero-Shot Segmentation Framework Leveraging GPT-Generated Semantic Embeddings and Relationship Alignment. The Visual Computer, 2025: 1-13.

[21] L, Davide; R, Livio. Fine-tuning GPT-3 for Legal Rule Classification. Computer Law & Security Review: The International Journal of Technology Law and Practice, 2023, 51.

[22] Shultz, R. T.; Wise, M. J.; Nobandegani, S. A. Text Understanding in GPT-4 Versus Humans. Royal Society Open Science, 2025, 12(2): 241313.

[23] F, Kexue; G, Peng; L, Shaolei. POS-BERT: Point Cloud One-Stage BERT Pre-Training. Expert Systems With Applications, 2024, 240.

[24] Paul, S.; Saha, S. CyberBERT: BERT for Cyberbullying Identification. Multimedia Systems, 2020 (prepublish): 1-8.

[25] Wada, S.; Takeda, T.; Okada, K. Oversampling Effect in Pretraining for Bidirectional Encoder Representations from Transformers (BERT) to Localize Medical BERT and Enhance Biomedical BERT. Artificial Intelligence In Medicine, 2024, 153: 102889.

[26] Gao, Z.; Feng, A.; Song, X. Target-Dependent Sentiment Classification With BERT. IEEE Access, 2019, 7: 154290-154299.

[27] Ethan, W.; Joshua, O.; Mouayad, M. Large Language Model (LLM)-Driven Chatbots for Neuro-Ophthalmic Medical Education[J]. Eye (London, England), 2023, 38(4): 639-641.

[28] Silva, L.; Barbosa, L. Improving Dense Retrieval Models with LLM Augmented Data for Dataset Search. Knowledge-Based Systems, 2024, 294: 111740.

[29] Bowlick, J.F.; Bednarz, W.S.; Goldberg, W.D. Student Learning in an Introductory GIS Course: Using a Project-Based Approach. Transactions in GIS, 2016, 20(2): 182 - 202.

[30] Mathews, J.A.; Wikle, A.T. GIS&T Pedagogies and Instructional Challenges in Higher Education: A Survey of Educators. Transactions in GIS, 2019, 23(5): 892 - 907.

[31] Hochmair, H.H. Use and Effectiveness of Chatbots as Support Tools in GIS Programming Course Assignments. ISPRS International Journal of Geo - Information, 2025, 14(4): 156 - 156.

[32] Wanwu, L.; Lin, L.; Hui, Z. Dynamic Map-Making Technology and the Application in Geographic Information Science. Computer Applications in Engineering Education, 2024, 32 (4).

[33] G, W. D.; B, J. F.; S, E. P. Virtualization in CyberGIS Instruction: Lessons Learned Constructing a Private Cloud to Support Development and Delivery of a WebGIS Course. Journal of Geography in Higher Education, 2021, 45(1): 128–154.

[34] Zhuge, Q.; Wang, H.; Chen, X. TwinStar: A Novel Design for Enhanced Test Question Generation Using Dual-LLM Engine. Applied Sciences, 2025, 15(6): 3055.

[35] G, Yunfan; X, Yun; W, Siqi. GeoBERT: Pre-Training Geospatial Representation Learning on Point-of-Interest. Applied Sciences, 2022, 12(24): 12942.

[36] Janarthanan, K. N. S.; Asaithambi, M. Recent Developments in Geographic Information Systems Across Different Application Domains: A Review. Knowledge and Information Systems, 2023, 66(3): 1523–1547.

[37] Duan, J.; Min, W.; Lin, D. Multimodal Graph Inference Network for Scene Graph Generation. Applied Intelligence, 2021, 51(12): 1–16.

[38] Huang, Y.; Glänzel, W.; Zhang, L. Tracing the Development of Mapping Knowledge Domains. Scientometrics, 2021, 126(7): 1–24.

[39] D'Anna, G.; Cauter, V. S.; Thurnher, M. Can Large Language Models Pass Official High-Grade Exams of the European Society of Neuroradiology Courses? A Direct Comparison Between OpenAI ChatGPT 3.5, OpenAI GPT4 and Google Bard[J].Neuroradiology, 2024, 66(8): 1245-1250.

[40] Luke, V. N. A. W.; Chong, S. L.; Ban, H. K. Is ChatGPT 'Ready' to Be a Learning Tool for Medical Undergraduates and Will It Perform Equally in Different Subjects? Comparative Study of ChatGPT Performance in Tutorial and Case-Based Learning Questions in Physiology and Biochemistry[J].Medical Teacher, 2024, 46(11): 1-7.

[41] Voultsiou, E.; Vrochidou, E.; Moussiades, L. The Potential of Large Language Models for Social Robots in Special Education. Progress in Artificial Intelligence 2025, (prepublish), 1–25.

[42] Rachida, S.; NasrEddine, T.; Cláudia, A.T. GIS-Based Expert Knowledge for Landslide Susceptibility Mapping (LSM): Case of Mostaganem Coast District, West of Algeria. Sustainability 2021, 13(2), 630.

[43] Zhang, Y.; Wei, C.; He, Z. GeoGPT: An Assistant for Understanding and Processing Geospatial Tasks. International Journal of Applied Earth Observation and Geoinformation 2024, 131, 103976.

[44] Mireia, E. The Use of Artificial Intelligence (AI) to Enhance Academic Communication, Education and Research: A Balanced Approach. The Journal of Hand Surgery, European Volume 2023, 48(8), 17531934231185746.