Building an Intelligent Diagnostic Paradigm for Urban Indicator Health Assessment by Integrating Large Language Models

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Abstract

In the context of digital and intelligent territorial spatial governance, urban health examination and evaluation is shifting from indicator monitoring toward comprehensive diagnosis. Yet indicator-centered assessment still tends to describe anomalies superficially, while the integration of data analytics and professional planning knowledge remains weak. This paper understands indicator-based assessment as a systematic cognitive process for interpreting the operating state of complex urban systems, and proposes an S-E-D diagnostic ontology composed of Symptom, Explanation, and Decision. On this basis, it develops a knowledge-enhanced large language model method that supports indicator analysis, causal explanation, and strategy generation under conditions of constrained planning knowledge through the structured processing of planning documents and technical standards. A case study of Nanjing shows that the proposed method performs well in multi-indicator integration, reasoning consistency, and the interpretability of strategic recommendations. The study offers a methodological reference for transforming urban indicator assessment from experience-dependent practice into reproducible and traceable intelligent diagnosis.

Keywords

city health examination and evaluation; territorial spatial governance; large language models; intelligent diagnosis

1 Background: The Digital and Intelligent Transformation of Urban Health Examination and Evaluation

1.1 Paradigm Shift: From Indicator Monitoring to Intelligent Cognition

Urban health examination and evaluation is an important tool for supervising the implementation of territorial spatial planning and for improving the quality of spatial governance. In recent years, with the gradual establishment of the "multi-plan integration" implementation monitoring system, city health examination has become a regular mechanism for understanding urban operation, identifying planning implementation problems, and supporting adaptive policy adjustment [1-3]. Local practices have developed around indicator examination, task examination, and thematic examination, among which indicator examination provides the most direct entry point for perceiving the operating state of urban space [4].

Traditional indicator assessment mainly relies on statistical comparison, target benchmarking, and periodic reporting. It is effective for recording whether a single indicator has reached a target, but it is less capable of explaining why deviations occur or how they should be addressed. With the expansion of digital infrastructure, spatiotemporal data, and urban operation platforms, indicator examination is moving from ex post statistical review toward dynamic sensing and continuous monitoring. The construction of the territorial spatial planning implementation monitoring network further strengthens the demand for real-time assessment, intelligent diagnosis, and decision support [5-7]. Under this trend, the core task of indicator examination is no longer merely to monitor values, but to build an intelligent cognitive process that integrates problem identification, mechanism explanation, and strategy generation.

1.2 Practical Constraints: Experience Dependence and Insufficient Knowledge Integration

Although multi-source data have improved the breadth and timeliness of indicator monitoring, the deeper diagnostic capacity of current practice remains constrained by two problems. First, diagnosis is still highly dependent on expert experience. Urban systems are complex, coupled, multi-scalar, and nonlinear; indicator changes may involve delayed effects, cross-sector interactions, and hidden causal links [8]. Planners often need to interpret fragmented and high-frequency data through professional judgment, but stable causal chains are difficult to extract directly. As a result, assessment conclusions may stop at a list of abnormal indicators and rely heavily on individual experience, making it difficult to identify structural causes and transferable decision rules [9].

Second, the integration of planning knowledge remains insufficient. Policy documents, technical guidelines, statutory plans, evaluation reports, and expert knowledge together constitute the professional logic of urban health diagnosis. Existing digital methods are usually strong in calculation and visualization, but weak in organizing unstructured planning texts and embedding them into reasoning processes. This produces a gap between monitoring data and professional planning knowledge [10]. Data-driven methods are not naturally able to represent institutional rules, planning mechanisms, and spatial governance logic, while traditional rule-based reasoning is limited when it needs to integrate heterogeneous knowledge sources [11]. A new framework is therefore needed to connect data correlations with knowledge constraints.

1.3 Technical Opportunity: Knowledge-Enhanced Intelligent Reasoning

Large language models provide a new technical opportunity for urban indicator diagnosis because of their capacity for semantic understanding, knowledge association, and natural-language generation. Knowledge-enhanced pre-trained language models, retrieval-augmented generation, dense retrieval, and agent-based reasoning have already been applied in fields such as finance, accounting, medicine, education, and programming assistance [13-21]. Their value lies not only in text generation, but also in organizing domain knowledge, retrieving relevant evidence, and building structured reasoning chains.

For urban health examination, large language models can combine planning texts, policy standards, indicator data, and contextual information, thereby supporting semantic interpretation and multi-step reasoning. However, existing applications in planning still focus mainly on policy interpretation, knowledge-based question answering, or isolated indicator explanation. They have not yet formed a complete paradigm that connects indicator understanding, causal explanation, and comprehensive planning judgment [22-23]. This paper therefore conceptualizes indicator examination as a cognitive diagnostic process for complex urban systems, constructs an S-E-D ontology, and explores a knowledge-enhanced large language model method for intelligent diagnosis.

2 Cognitive Ontology Construction and Knowledge Enhancement Mechanism

2.1 Reconstructing the Diagnostic Ontology: The S-E-D Cognitive Ontology

Urban indicator examination should be understood not as simple technical monitoring, but as a comprehensive diagnostic process oriented toward complex adaptive urban systems [24]. Its object is not the static comparison of isolated indicators, but the coupling relationships, deviations, and risks among spatial, social, economic, ecological, and institutional subsystems [25-26]. Traditional benchmarking and linear weighting can determine whether an indicator deviates from a target, but cannot adequately explain the causes, pathways, and governance implications of that deviation.

To respond to this limitation, this paper proposes an S-E-D cognitive ontology for indicator diagnosis: Symptom, Explanation, and Decision. The ontology reorganizes the assessment process into a closed cognitive chain from state perception to mechanism attribution and then to planning response.

2.1.1 Symptom Layer: State Perception and Deviation Identification

The symptom layer translates the operating state of the city into recognizable and comparable problem signals. It identifies whether indicators deviate from planning goals, technical standards, historical trajectories, or expected ranges, and it pays attention to temporal dynamics and inter-indicator associations. Compared with static value comparison, this layer emphasizes the semantic meaning of indicators in specific planning contexts. Its output is a set of structured symptom units, such as decline, fluctuation, mismatch, threshold pressure, or insufficient coordination.

2.1.2 Explanation Layer: Cause Understanding and Mechanism Attribution

The explanation layer moves the analysis from "what has changed" to "why it has changed." It links abnormal indicator performance with spatial structure, resource endowment, development stage, institutional constraints, and socioeconomic processes. Through planning knowledge constraints, the model can avoid generalized explanations detached from local context and instead transform abnormal values into causal interpretations with traceable evidence. This layer is the key bridge between data monitoring and professional planning judgment.

2.1.3 Decision Layer: Strategy Generation and Decision Output

The decision layer converts diagnostic cognition into governance strategies. Strategy generation should correspond to identified causes, planning objectives, institutional conditions, and implementation pathways. It should not merely produce generic recommendations, but should organize countermeasures according to the chain of symptom recognition, mechanism diagnosis, and strategic intervention. In this sense, indicator examination becomes a process of evidence-based planning reasoning rather than a descriptive assessment report.

2.2 Intelligent Reasoning Under Knowledge Constraints

The knowledge-enhanced reasoning path contains three linked processes. The first is knowledge modeling and structured organization. Planning documents, technical standards, policy texts, evaluation reports, and expert experience are cleaned, segmented, normalized, and transformed into computable semantic units. Embedding models such as S-BERT and BGE can map these units into dense vector spaces and form a domain-specific planning knowledge base [27-30].

The second process is semantic retrieval and dynamic knowledge scheduling. When an indicator anomaly is detected, the system retrieves highly relevant knowledge fragments according to the indicator type, planning object, spatial context, and problem description. Dense vector retrieval can capture semantic similarity, while sparse keyword retrieval and symbolic constraints can maintain precise matching with local policy terms, standards, and planning categories [31-32].

The third process is fusion generation and reasoning control. Retrieval-augmented generation introduces planning evidence into the model context, while structured prompts guide the model to follow the S-E-D reasoning chain [33-36]. Generation hyperparameters further constrain sampling behavior so that the output remains stable, coherent, and grounded in retrieved knowledge. Compared with domain fine-tuning, this approach has lower training cost and reduces the risk of overfitting. It changes the role of the model from storing planning knowledge internally to invoking, organizing, and reasoning with external planning knowledge.

Table 1. Large language model generation hyperparameter configuration and regulation mechanisms.

Parameter	Value	Range	Function	Regulation mechanism
Temperature	0.3	0-2	Controls randomness and diversity in generation	A lower value is used to improve reasoning stability and logical consistency.
Top P	0.1	0-1	Truncates candidate tokens by cumulative probability	The candidate space is compressed, low-probability expressions are reduced, and output determinacy is strengthened.
Frequency penalty	0	0-1	Reduces the probability of repeatedly generated high-frequency words	Term recurrence is preserved to maintain consistency in structured diagnostic expression.
Presence penalty	0	0-1	Encourages the introduction of new content	The value is set to avoid deviation from retrieved knowledge and to keep the analysis centered on the given information.
Max tokens	16384	0-16384	Controls the maximum length of one generation	The setting supports long-text input and multi-step reasoning.

3 Intelligent Reasoning Method Based on the S-E-D Ontology

This paper develops a large-language-model-centered intelligent reasoning method for indicator-based urban health assessment. The method integrates a planning knowledge base, contextual indicator information, and constrained reasoning prompts, guiding the model through the chain of symptom analysis, explanatory attribution, and decision generation. The goal is to make indicator diagnosis more reproducible, traceable, and interpretable.

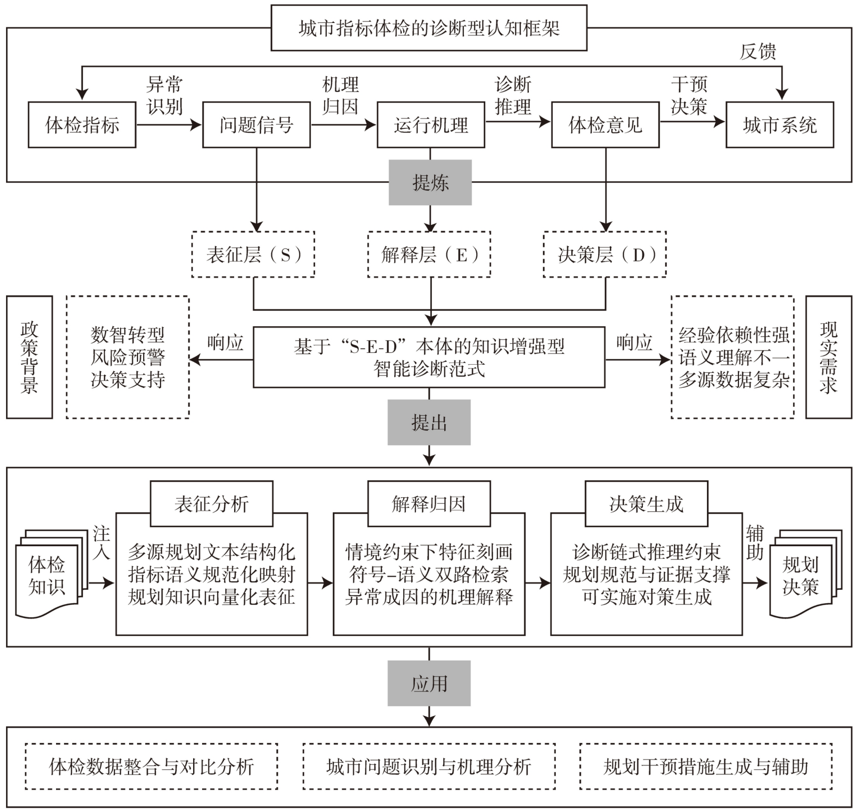

Figure 1. Technical framework of intelligent diagnosis for indicator-based urban health assessment based on the S-E-D cognitive closed loop.

3.1 Symptom Analysis: Constructing the Planning Knowledge Base

Symptom analysis begins with the construction of a planning knowledge base. Policy documents, technical procedures, statutory planning texts, and health examination reports are transformed into retrievable and computable knowledge units through text cleaning, structural parsing, and terminology normalization. Indicator data are tagged by category, year, value, standard, threshold, and planning target, while planning texts are decomposed into semantic elements such as object, state, problem, cause, and countermeasure.

To support accurate retrieval and contextual reconstruction, the knowledge base adopts a two-level semantic structure. The upper level records the thematic domain, planning object, and institutional source of each knowledge unit; the lower level records the corresponding diagnostic meaning, causal logic, and policy response. After vectorization, the database can support similarity search, evidence retrieval, and the assembly of context for model reasoning.

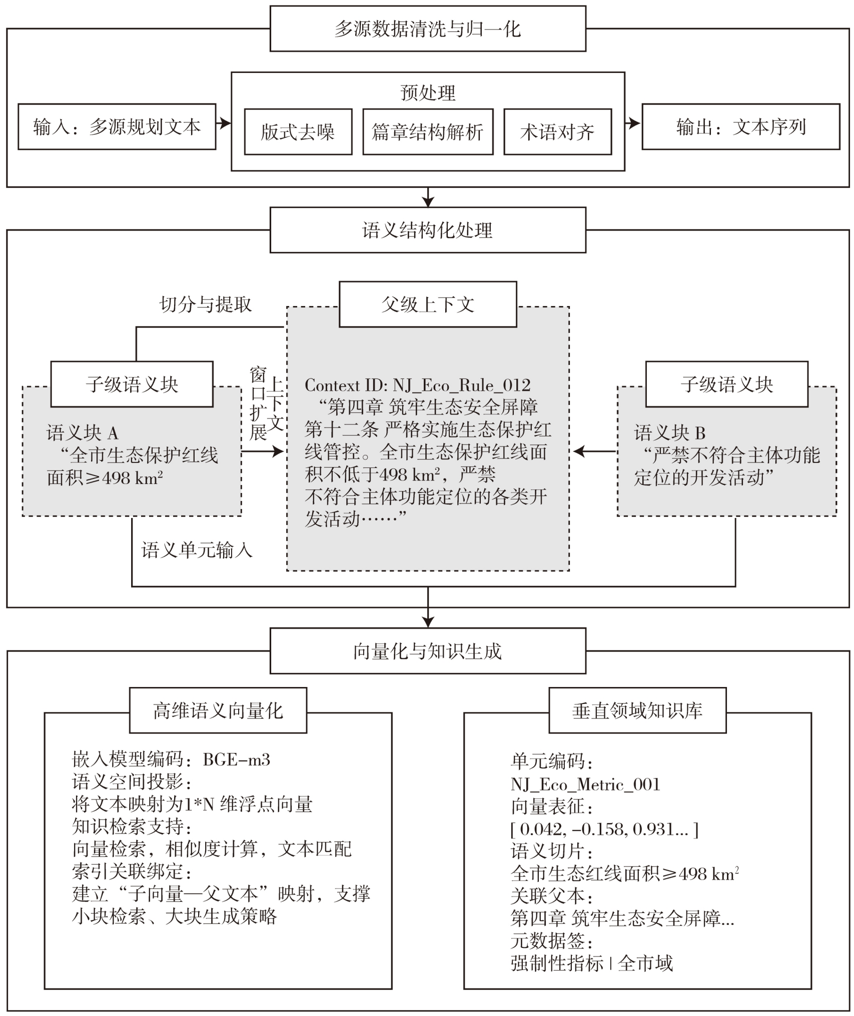

Figure 2. Semantic deconstruction and database construction process of the planning knowledge base for indicator-based diagnosis.

3.2 Explanatory Attribution: Knowledge-Driven Retrieval Strategy

After abnormal indicators are identified, the focus of analysis shifts from whether an anomaly exists to why it has occurred. To prevent a general model from producing context-free explanations, the proposed method places indicator changes within local conditions, functional attributes, development stages, and institutional constraints through the planning knowledge base. Retrieval proceeds through a combination of symbolic constraints and semantic similarity. Symbolic constraints narrow the object domain and ensure that the retrieved evidence corresponds to the correct planning category, spatial unit, and policy context. Semantic similarity then captures the association between indicator anomalies and relevant planning knowledge. Weighted fusion produces a set of evidence fragments that support causal interpretation.

3.3 Decision Generation: An Evidence-Based Diagnostic Reasoning Paradigm

Decision generation follows symptom identification and causal explanation. It converts the diagnosis into planning strategies and governance recommendations. The structured prompt template embeds indicator recognition, cause analysis, and countermeasure generation into the reasoning process, while retrieved knowledge provides normative standards, policy bases, and local planning constraints. Through retrieval-augmented generation and hyperparameter control, the model reduces unsupported leaps and evidence gaps. The resulting output is more traceable and more suitable for planning practice.

4 Empirical Study: Experimental Exploration in Nanjing

4.1 Study Area and Indicator System

Nanjing, the capital of Jiangsu Province, is located in the lower Yangtze River and Jianghuai region and is a core hub city in the Yangtze River Delta. By the end of 2024, its permanent resident population reached 9.577 million, and its urbanization rate was 87.3%. Since 2019, Nanjing has continuously advanced urban health examination and evaluation, forming relatively stable indicator data and annual assessment reports. This provides a suitable basis for testing intelligent diagnosis.

The experiment selected basic indicators closely related to territorial spatial planning and with continuous comparable data. After excluding two indicators with discontinuous data, 29 experimental indicators were retained. The study organized Nanjing's urban health examination reports from 2019 to 2023 and integrated 59 core policy and planning documents to build a structured planning knowledge base and a standard-policy knowledge base.

Table 2. Composition of the 2023 Nanjing city health examination and evaluation indicator system.

Component	Composition retained for this experiment	Diagnostic role
First-level dimensions	Safety, innovation, coordination, green development, openness, and sharing	Provide the overall structure for evaluating urban operation.
Indicator type	Basic indicators and recommended indicators	Distinguish mandatory monitoring items from locally extended assessment items.
Experimental indicator sample	29 basic indicators retained after excluding two indicators with discontinuous data	Support cross-year comparison and model-based reasoning.
Knowledge materials	2019-2023 assessment reports and 59 core policy and planning documents	Provide local evidence, policy constraints, and planning interpretation bases.

4.2 Experimental Verification Based on the S-E-D Ontology

The experiment used a 671B-parameter DeepSeek knowledge-enhanced large language model. The model was required to diagnose indicator performance according to the S-E-D ontology, retrieve relevant planning knowledge, and generate explanations and strategies with explicit evidence.

4.2.1 Indicator Identification and Information Invocation

The ecological conservation redline area provides a representative example. The knowledge base identifies the normative benchmark for this indicator as "no reduction, with stability or moderate increase where conditions permit." The data show that Nanjing's ecological conservation redline area was 505.74 km2 in 2020, declined to 496.64 km2 in 2022, and recovered slightly to 498 km2 in 2024.

The model recognized a pattern of initial expansion, subsequent decline, and slight recovery. When this trend was considered alongside the stabilization or slight decline of urban and rural construction land, the model judged that spatial development pressure remained, but that the policy bottom line had not been fundamentally breached. The output combined state recognition, temporal trend judgment, and compliance assessment.

4.2.2 Problem Explanation and Causal Reasoning

In the explanatory stage, the model integrated indicators related to safety, ecology, land use, innovation, and spatial development. It placed abnormal values within Nanjing's resource conditions, development stage, and institutional constraints. For example, indicators concerning permanent basic farmland, groundwater level, and construction land expansion were associated with natural resource constraints and insufficient allocation of construction land, revealing pressures on land and ecological security. The growth of urban and rural construction land, the decline in the proportion of industrial land, and the low efficiency of idle land disposal suggested that industrial restructuring and stock land renewal lagged behind the needs of innovation-driven development. Indicators such as population density, building density, and public service provision showed that new-town expansion was faster than population and function import, reflecting insufficient coordination among plans and stronger district-level decision autonomy.

Through this process, the model transformed indicator anomalies into traceable causal explanations rather than isolated descriptive judgments.

Table 3. Examples of multi-layer mapping relationships between indicators and knowledge.

Typical indicator	Symptom meaning	Possible cause and knowledge basis	Strategy orientation
Permanent basic farmland	Reflects the bottom line of cultivated-land protection and agricultural spatial security	Staged decline may indicate pressure from construction expansion or insufficient supplementary cultivated-land mechanisms; the interpretation is constrained by cultivated-land protection policy and territorial spatial planning requirements.	Strengthen permanent basic farmland protection, improve high-standard farmland construction, and coordinate supplementary cultivated-land implementation.
Urban waterlogging points	Reflects drainage resilience, flood-control capacity, and infrastructure operation	Waterlogging may be associated with aging pipe networks, insufficient rainwater detention capacity, and	Promote sponge-city construction, remediate waterlogging points, renew drainage networks, and improve

		weak smart monitoring; evidence is linked to sponge-city standards and drainage-system planning.	smart monitoring and early-warning systems.

4.2.3 Strategy Integration and Decision Output

At the decision stage, the model generated strategic recommendations through cross-year and cross-dimensional integration. For innovation-related indicators, it connected the decline in industrial land share, stock land inefficiency, and the spatial mismatch between innovation functions and public services. It proposed improving the activation mechanism for stock land, coordinating the layout of industrial and innovation spaces, strengthening the connection between innovation districts, public services, and transport networks, and refining policy support and monitoring mechanisms. Compared with general recommendations, these outputs were more clearly linked to indicator evidence and planning constraints.

4.3 Comparative Analysis of Model Capabilities

4.3.1 Experimental Design and Evaluation Framework

To compare the capabilities of a pre-trained large language model and the knowledge-enhanced model, the study constructed a hierarchical evaluation framework. The test included 50 objective questions and 5 essay questions. The objective questions examined indicator recognition, policy-text matching, normative mapping, and cross-period reasoning. The essay questions examined multi-indicator integration, problem attribution, and decision support. Expert evaluation considered response effectiveness, logical clarity, absence of obvious errors, willingness to adopt, confidence in evaluation, and overall preference.

Table 4. Hierarchical evaluation framework.

Evaluation layer	Question design	Capability tested
Basic identification	Objective questions on indicator meaning and policy-text matching	Indicator recognition, information retrieval, and local policy matching
Normative mapping and cross-period reasoning	Objective questions on standards, temporal comparison, and institutional applicability	Rule matching, cross-period logic, and evidence consistency
Integrated diagnosis	Five essay questions	Multi-indicator identification, causal attribution, and integrated decision support

4.3.2 Objective-Test Results and Analysis

The objective-test results show that the two models differed most clearly in tasks requiring local policy understanding and cross-period reasoning. In questions concerning local policy-text matching and basic indicator recognition, both models performed relatively stably. The pre-trained model made one error by incorrectly associating a local context with other cities, indicating a risk of semantic drift when multiple local documents are involved.

In normative mapping and cross-period reasoning, the pre-trained model made four errors. Its weaknesses were concentrated in unclear institutional applicability, insufficient use of key evidence, and unstable temporal inference. The knowledge-enhanced model maintained better correctness in this part, suggesting that the knowledge base provided effective semantic anchors and reasoning constraints.

4.3.3 Subjective-Test Performance and Analysis

The subjective evaluation further confirms the advantage of the knowledge-enhanced model. Overall, evaluators preferred the knowledge-enhanced model in 54.5% of comparisons, preferred the pre-trained model in 28.9%, and judged the two to be similar in 16.7%. Strong preference for the knowledge-enhanced model was also higher than that for the pre-trained model. The knowledge-enhanced model scored better in response effectiveness, logical clarity, absence of obvious errors, willingness to adopt, and evaluator confidence.

Evaluator expertise affected the results. Respondents familiar with urban health examination and planning diagnosis were more likely to prefer the knowledge-enhanced model; in the high-familiarity group, the preference rate reached 86.7%. Professional evaluators paid more attention to indicator evidence and data support and were better able to identify the generalization and evidence gaps of the pre-trained model. Less familiar users were more easily influenced by fluency and apparent completeness. This indicates that knowledge enhancement improves information density, logical completeness, and decision-support potential, but its value is most evident when the task requires professional judgment.

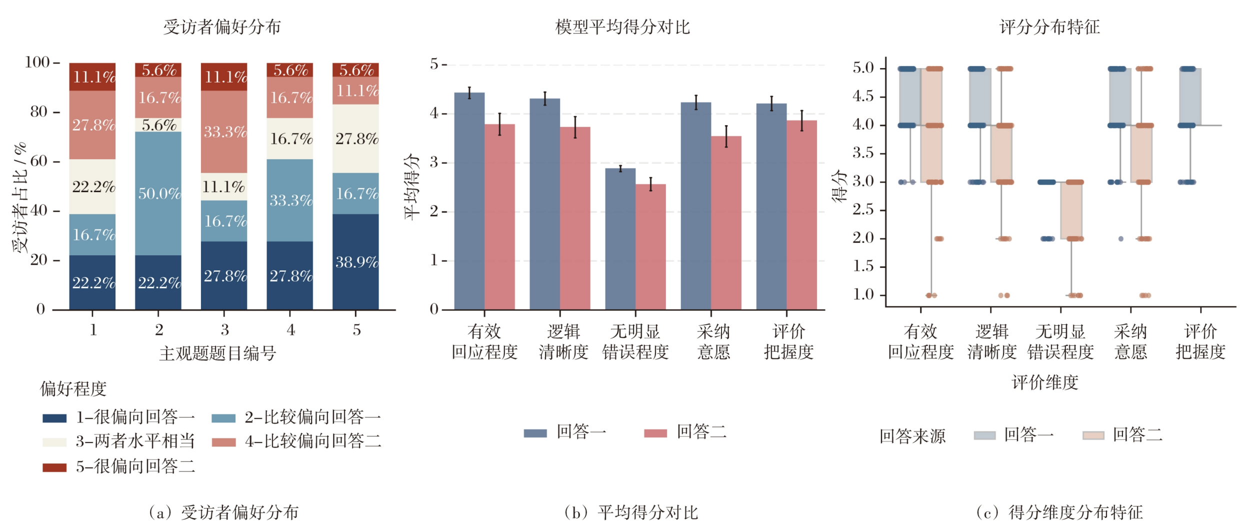

Figure 3. Comparative analysis of subjective-question performance.

5 Conclusions and Prospects

This study argues that the central challenge of urban health examination and evaluation is not only data acquisition, but the reasoning linkage among indicator monitoring, professional knowledge, and planning judgment. It reconceptualizes indicator examination as a diagnostic process moving from symptom recognition to explanatory attribution and then to decision generation. Based on this understanding, it proposes the S-E-D cognitive ontology and a knowledge-enhanced large language model method.

The method structures planning knowledge and context constraints so that the model's generation is bounded by planning evidence, institutional logic, and local professional context. It supports cross-indicator integration, problem attribution, and strategy reasoning. The Nanjing experiment shows that the knowledge-enhanced mechanism provides semantic anchors and reasoning constraints, improving stability and accuracy in local context understanding, normative knowledge matching, and cross-period logical reasoning. Compared with the pre-trained model, the knowledge-enhanced model produced outputs with stronger data support, deeper analysis, and better decision-support value.

At the same time, the improvement is not uniform across all tasks. The method performs better in quantitative, local, and evidence-rich tasks, but still faces limitations in abstract spatial inference, complex causal reasoning, and expression optimization. Knowledge-enhanced large language models cannot replace expert judgment; rather, they provide a structured auxiliary mechanism for professional diagnosis. The construction and updating of the knowledge base still depend partly on manual or semi-automatic work, and dynamic adaptation needs further improvement. The empirical test is based on a single city, and cross-regional applicability requires additional verification. Future research should strengthen multimodal knowledge fusion, multi-city comparative validation, and evidence-driven generation mechanisms, so as to support a more robust intelligent diagnostic system for territorial spatial governance.

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AI-assisted translation