Theoretical Paradigm and Methodology of AI-assisted Territorial Spatial Diagnosis

LIU Xiaochang, WU Zhiqiang

Abstract: Faced with the complex urban diseases that emerge within territorial space, territorial spatial diagnosis often falls into fragmented symptomatic treatment and hurried experience-based decision-making during fast-moving planning practice, which may turn spatial planning into an abstract exercise detached from reality. Although AI technologies with higher-level holistic reasoning and ecological rationality show substantial potential for improving the scientific rationality of territorial spatial planning, effective theoretical paradigms and operational methods for AI-assisted territorial spatial diagnosis remain insufficient. Starting from the theoretical characteristics and core tasks of territorial spatial diagnosis, this paper reviews the development trajectory of diagnostic technologies and identifies the challenges facing their intelligent transformation. On this basis, it constructs a Dual-Helix paradigm and a Diamond framework for territorial spatial diagnosis under human-machine hybrid intelligence, and further proposes five directions for changes in cognitive and action methods and six systems for enhancing working methods after AI is introduced into territorial spatial diagnosis. The proposed framework is expected to systematically address the problems and symptoms of traditional territorial spatial diagnosis, improve the scientific rationality of territorial spatial planning, and promote the sustainable development of territorial space.

Keywords: territorial spatial diagnosis; artificial intelligence technology; theoretical paradigm; cognitive and action methods; spatial laws; human-machine hybrid intelligence

Since the reform and opening-up period, China's territorial space has undergone rapid urbanization on a scale rarely seen in human history. Various negative effects and urban diseases have emerged and now pose serious threats to the sustainable development of territorial space. When facing highly diverse spatial disorders, territorial spatial diagnosis often treats symptoms in a fragmented way and relies on hurried experience-based decisions in fast-moving spatial planning practice. This can turn spatial planning into an abstract exercise detached from actual conditions.

To further improve the rationality of spatial planning, scholars in the field have explored the intellectual foundations of territorial spatial diagnosis and its supporting technologies, including digitalization, informatization and intelligentization [1]. The planning profession has also issued standards related to territorial spatial health examination and evaluation [2]. A theoretical, methodological and technical system for identifying and preventing territorial spatial disorders has therefore gradually taken shape.

The supporting technologies for territorial spatial diagnosis can be broadly divided into two types. The first is knowledge-driven technology. Territorial spatial health examination and evaluation, for example, builds expert knowledge bases, extracts knowledge into indicator systems and specific indicator settings, and then uses these standards to conduct examinations and evaluations [3-5]. Planning support systems based on if-then-else rules similarly translate knowledge into standardized rules executable by machines [6-7]. The second is data-driven technology. Machine learning no longer relies only on explicitly extracted knowledge; through training, validation and testing on massive datasets, it obtains knowledge that is full-sample rather than sample-based, efficiency-oriented rather than precision-oriented, and correlation-based rather than causality-based, and then uses it for problem diagnosis [7-8]. Recent AIGC technologies, including DeepSeek, ChatGPT, Midjourney and Gemini, build on general large models and incorporate training techniques, retrieval-augmented generation and agents. They make it possible to construct professional and industrial large models for spatial planning and to generate diverse outputs such as territorial spatial health examination reports [9].

However, when these two types of supporting technologies are examined together, many practical difficulties remain. The difficulty of knowledge-driven technology lies in the effective extraction and accurate expression of knowledge. This difficulty originates in the integral, inclusive, balanced, law-oriented, ecological and sustainable characteristics of spatial planning [10]. Data-driven technology avoids the problem of knowledge extraction and expression, but black-box knowledge still creates limitations in data dependence, result interpretation, cognitive transfer and decision credibility, and therefore cannot comprehensively improve the scientificity of territorial spatial diagnosis [11].

Even so, the wave of AI technology in spatial planning continues to develop and has exerted an increasingly profound influence on territorial spatial diagnosis [8, 10]. Against this background, it is necessary to reconsider the application of AI in this field. How can a theoretical paradigm and model architecture for AI-assisted territorial spatial diagnosis be systematically constructed? How can the changes in cognitive and action methods after AI intervention be fully clarified? These questions are central to overcoming the technical rationality deficits of traditional territorial spatial diagnosis, including difficulty in perceiving public concerns, tracing flows, distinguishing trajectories, following laws and demonstrating effects [12].

1 Theoretical Characteristics and Main Tasks of Territorial Spatial Diagnosis

1.1 Theoretical Characteristics of Territorial Spatial Diagnosis

1.1.1 Orientation toward Objective Laws

Deductive reasoning is one of the most commonly used methods in clinical diagnosis, and it offers an effective reference for the theoretical characteristics of territorial spatial diagnosis [13]. Deductive reasoning starts from common or universal laws and, by comparing them with diagnostic criteria [14], reaches an understanding of individual objects [15].

The basic assumption of territorial spatial diagnosis is that territorial space is a living body with its own objective laws of development and evolution. Diagnosis determines whether these laws have been deviated from, the degree of deviation and the causes of such deviation. Territorial spatial diagnosis should therefore recognize, respect and follow the laws of territorial spatial development and evolution [16], allocate limited resources to the disorders that most seriously deviate from these laws, and avoid exaggerated diagnosis or fragmented judgments.

1.1.2 Orientation toward Multiple Coordination

Evidence-based medicine also provides an important reference for the theoretical characteristics of territorial spatial diagnosis. External clinical evidence can inform practice, but it can never replace professional knowledge in individual clinical contexts. It is this professional knowledge that determines whether external evidence applies to a specific patient. Likewise, when deciding whether and how to match a patient's clinical condition, context and preferences, any external guideline must be integrated with the clinician's expertise. The core idea of evidence-based medicine is therefore to combine clinical evidence, physician experience and patient preferences in the collaborative formulation of medical decisions [17].

By analogy, territorial spatial diagnosis combines the evidence body of spatial disorders, the practical experience of planners and the urgent concerns of stakeholders. On this basis, it collaboratively formulates diagnostic methods and treatment plans for territorial spatial disorders, so as to achieve the best possible diagnostic and therapeutic effect.

1.1.3 Orientation toward Temporal Evolution

Medical history taking is another common method in clinical diagnosis. A medical history mainly records symptoms and the process and outcome of their occurrence, development, diagnosis and treatment [18], thereby supporting accurate disease diagnosis and treatment [14].
Similarly, territorial space is a complex living body composed of countless processes and elements. Its evolutionary process involves concepts such as criticality, threshold, surprise and phase transition [19]. Territorial spatial diagnosis therefore does more than judge present problems. It also considers the timing, development process and treatment plan of spatial disorders, and further simulates the evolution of disorders under different treatment plans. In this way, it anticipates different treatment effects and shifts territorial spatial diagnosis from a past- and present-oriented practice toward future-oriented diagnosis.

1.1.4 Orientation toward the Mutual Formation of Forms and Flows

Territorial spatial planning takes spatial forms as the main object of management and intervention, while the orderly and efficient operation of flows in space is a deeper goal of territorial spatial planning [20]. The mutual formation of forms and flows treats territorial space as a living body and emphasizes flows with objective natural attributes, subjective mobility intentions and value standards [1]. The object of territorial spatial diagnosis is therefore not only forms such as buildings, rivers and roads, but also natural flows, people flows, logistics flows, economic flows, functional flows and information flows, as well as the interactions between forms and flows.

1.2 Main Task Stages of Territorial Spatial Diagnosis

In modern medicine, disease diagnosis generally includes collecting clinical data; analyzing, synthesizing and evaluating data; proposing a preliminary diagnosis; and verifying or revising the diagnosis [14]. This procedure for understanding disease cannot be omitted, skipped or casually reversed. Drawing on this workflow, territorial spatial diagnosis can be divided into five tasks: feeling perception, evidence learning, explanatory inference, prognostic judgment and prescription making.
Feeling perception obtains relevant data and information about territorial space. Evidence learning mines the laws of territorial spatial development and evolution as diagnostic criteria. Explanatory inference identifies the degree of deviation from these laws and the causes of deviation. Prognostic judgment simulates short- and long-term effects after spatial self-recovery or intervention, including recovery, transition and progression. Prescription making supplements and revises spatial self-recovery or planning intervention and proposes optimization strategies.

2 Development Trajectory of Territorial Spatial Diagnostic Technologies and Challenges of Intelligent Transformation

2.1 Three Stages in the Development of Territorial Spatial Diagnostic Technologies

The development trajectory of territorial spatial diagnostic technologies can be divided into three stages.

2.1.1 Stage I: Case Experience and Manual Investigation Technology

A common method of territorial spatial diagnosis is to take case materials as research objects, summarize experience from them and form possible causal conclusions [1]. However, the rationality of this approach is constrained by the knowledge accumulation of practitioners. It faces both the difficulty of verification and the limitation of falsification [21], and is often criticized for strong subjectivity, high arbitrariness and weak scientificity [22].

2.1.2 Stage II: Data Visualization, Expert Systems and Model Algorithms

With the rapid development of location-based geographic datasets such as mobile signaling data [23], GPS data [24], taxi trajectories [25], bus smart-card data [26] and points of interest (POI) [27], data visualization technology has provided new perspectives and methods for observing, understanding and analyzing territorial spatial problems [1]. It marks a key transition from perception to cognition [28].

Professional model technology introduces mathematical statistics to perform complex computation within a clear theoretical framework. For example, Yu Yajuan et al. [29] constructed an integrated evaluation model for territorial spatial health that combines trapezoidal membership functions, an improved mean square deviation method and weighted Euclidean distance. Wu Zhiqiang et al. [5] used projection pursuit to diagnose the ecological, economic and social benefits of territorial spatial use in China.

General decision support technology integrates computer technology on the basis of data visualization and professional modeling to form perception-action planning support systems [30-31], thereby providing scientific and rational support for territorial spatial diagnosis. Klosterman [6], for example, developed the land carrying-capacity diagnosis system WHAT IF. General decision support technology has also produced notable achievements in later diagnostic stages. Li Xia et al. [32] used cellular automata to analyze mechanisms of territorial spatial growth. Overall, general decision support technology ranks alternative decisions according to certain rules and decision objectives, and is an action based on knowledge representation and reasoning [33].

Tab. 1 Comparison of applicability conditions, mechanism logic and core capabilities across three stages of territorial spatial diagnostic technologies

Item	**Stage I: Case experience**	**Stage II: Data visualization and professional models**	**Stage II: General decision support**	**Stage III: AI technology**
Problem type	Problems highly similar to historical cases and weakly structured.	Information display, pattern discovery, preliminary diagnosis and rule-based evaluation.	Diagnosis and dynamic simulation under preset scenarios.	High-dimensional, nonlinear and complex patterns with unclear or undefined rules.
Data condition	Qualitative experience and historical case repositories.	Structured quantitative spatiotemporal data or data matching model assumptions.	Structured data defining parameters, rules and initial conditions.	Massive, multi-source and heterogeneous data.
Knowledge basis	Tacit knowledge and accumulated experience of planners.	Planner interpretation of visual information and explicit expert rules embedded in models.	Expert-defined interaction rules, weights and scenario frameworks.	Domain knowledge can be learned automatically from data.
Mechanism logic	Analogical reasoning and expert heuristics.	Information mapping, rule-driven symbolic reasoning and mathematical evaluation.	Scenario simulation and interactive computation.	Training, validation and testing driven by big data.
Perception	Weak, easily omitting implicit information.	Strong for spatial distribution and statistical features within preset indicators.	Moderate, with weak perception of unconventional data.	Strong, integrating structured and unstructured data.
Learning	Weak, difficult to discover complex mathematical laws.	Weak, because rules are fixed.	Weak, rules are set by experts.	Strong, automatically learning complex nonlinear laws.
Explanation	Strong in qualitative attribution but low in quantitative precision.	Strong when diagnosis follows explicit rules; weaker for automatic attribution.	Moderate, with attribution dependent on manual settings.	Can identify associations, but black-box features constrain interpretability.
Prognosis	Weak, limited to analogy with historical cases.	Limited to static inference within rules.	Strong for dynamic processes under preset rules.	Strong for predicting high-dimensional complex systems and exploring unknown scenarios.
Prescription	Moderate, producing experience-based suggestions.	Standardized rule-based strategies with limited flexibility.	Can evaluate plans but cannot generate adaptive strategies.	Supports multi-objective optimization, with reliability constrained by black-box features.

2.1.3 Stage III: Artificial Intelligence Technology

AI technology forms strong learners by combining weak learners in different ways to perform complex computation, learning and reasoning. It mainly includes machine learning, deep learning and reinforcement learning. Machine learning uses input control factors and output solutions as training data, calculates the mapping between inputs and outputs, and has been widely used in identifying territorial spatial functions and evaluating use benefits [33]. Common algorithms include decision trees and support vector machines [27, 34-36].

Deep learning adopts multi-layer hidden architectures and a hierarchical pretraining strategy that includes discriminative, generative and hybrid forms. It effectively strengthens feature extraction and law learning [37], and has broad applications in territorial spatial image processing, analysis, understanding and cognition [38]. Common algorithms include deep belief networks and convolutional neural networks [39]. Reinforcement learning maximizes the cumulative reward obtained by an agent from its environment so that it can learn an optimal strategy for achieving a goal. It places greater emphasis on learning strategies for solving territorial spatial diagnostic problems, and commonly uses algorithms such as Q-learning and actor-critic methods [40]. Overall, AI technology is nonlinear, adaptively learning and multidirectional. It can handle complex scenarios and has substantial potential in territorial spatial diagnosis.

2.1.4 Differences in the Applicability, Mechanisms and Core Capabilities of the Three Stages

The comparison of the three stages shows that AI technology differs fundamentally in applicability conditions, mechanism logic and core capabilities (Table 1). It can more effectively compensate for the technical rationality deficits of traditional territorial spatial diagnosis and lays an important foundation for constructing the theoretical paradigm of AI-assisted territorial spatial diagnosis.

2.2 Limitations in the Intelligent Transformation of Territorial Spatial Diagnostic Technologies

Although intelligent technologies provide useful support for territorial spatial diagnosis, it remains necessary to ask whether these technologies truly match its theoretical characteristics and whether they enhance its core tasks. At present, the limitations in the intelligent transformation of territorial spatial diagnostic technologies can be summarized in four aspects.

2.2.1 Limitation I: Insufficient Attention to the Life-like Characteristics of Space

At the macro level, current studies of territorial spatial diagnosis mainly address territorial spatial ecosystems [29], use performance and obstacle-factor diagnosis [41]. At the micro level, they mainly address functional location [42], public open space [43] and community environmental diagnosis [44]. Overall, most studies focus on a particular planning system, subsystem or spatial type. Although scholars have conducted systematic bionic analysis of the functional architecture of territorial spatial diagnosis [1], systematic theoretical frameworks oriented toward the life-like characteristics of space remain insufficient. The introduction of AI into territorial spatial diagnosis must therefore return to the philosophical premise that territorial space is a complex living body containing countless processes and elements, so as to enhance theoretical characteristics such as objective laws, multiple coordination, temporal evolution and the mutual formation of forms and flows.

2.2.2 Limitation II: Insufficient Attention to Objective Spatial Laws

Classical diagnostic technologies often calculate the mean or median of comparable evidence samples as a norm. This norm changes with the overall level of evidence bodies in the same period and is less restricted by the bias caused by a standard value based on experience. However, the input samples often lack interpretability with regard to the decision process and its basis. As a result, diagnostic standards oriented toward objective spatial laws remain absent, which can lead to exaggerated diagnosis or fragmented judgments. The reasons are threefold. First, AI technologies have not fully served the mining of objective laws and the formulation of evaluation standards. Second, research on AI technology has paid limited attention to helping people understand the decision process and basis for each input sample [45]. Third, trustworthy, reliable and explainable AI technologies have not been fully applied to the mechanisms, effects and optimization strategies that territorial spatial diagnosis is concerned with.

2.2.3 Limitation III: Insufficient Evidence-based Hybrid Intelligence

Current territorial spatial diagnosis can be summarized into two modes: humans input data and machines passively execute; or human consciousness is ignored and machines directly generate outputs. The methods used by AI models are essentially empirical and feedback-based methods such as classification, induction and trial and error. They are methodologically incomplete for territorial spatial diagnosis and depend heavily on past similar experience and human data annotation. The intelligence they simulate can often only be generalized to limited similar domains, namely local generalization, and is difficult to extend to all domains, namely global generalization. Its resistance to changing conditions is therefore limited. Human-machine collaboration is required when generating data, developing algorithms and evaluating results.

2.2.4 Limitation IV: Lack of a Task-oriented Closed-loop Technical Framework

On one hand, existing studies of territorial spatial diagnosis are fragmented and scattered. They often make deep breakthroughs on specific problems in a certain system, but lack an overall technical-system framework. On the other hand, diagnostic technologies often focus on improving their own algorithms, computing power and data, while lacking technical frameworks oriented toward the main tasks of territorial spatial diagnosis, including feeling perception, evidence learning, explanatory inference, prognostic judgment and prescription making. The reasons are also threefold. First, the technical objective is not centered on serving the core tasks of territorial spatial diagnosis. Second, spatial planning practitioners have limited understanding of the theoretical paradigm and thinking methods of AI-assisted territorial spatial diagnosis. Third, relevant algorithms have not yet been precisely matched with the core diagnostic tasks.

3 Theoretical Paradigm and Model Architecture for AI-assisted Territorial Spatial Diagnosis

3.1 The Dual-Helix Paradigm of AI-assisted Territorial Spatial Diagnosis

In territorial spatial diagnosis, AI intervention should follow four principles.

Principle 1 is data-centric AI. Based on prior knowledge, the focus shifts toward enhancing and enriching effective data for training algorithms.

Principle 2 is model-centric AI. By capturing relevant AI or causal relationships, it improves interpretability, robustness and adaptability, and reduces systematic AI bias.

Principle 3 is applications-centric AI. It requires a clear understanding of how territorial spatial planning makes decisions and how territorial spatial diagnosis can improve the scientific rationality of planning.

Principle 4 is human-centric AI. Its purpose is to empower human decision-making, not to replace it.

3.2 The Diamond Framework of AI-assisted Territorial Spatial Diagnosis

In existing studies, AI technology is usually incorporated into the research field of new technologies for territorial spatial planning, while a dedicated theory of intelligent territorial spatial diagnosis has not yet been formed. This study proposes the Dual-Helix paradigm of AI-assisted territorial spatial diagnosis (Fig. 1).

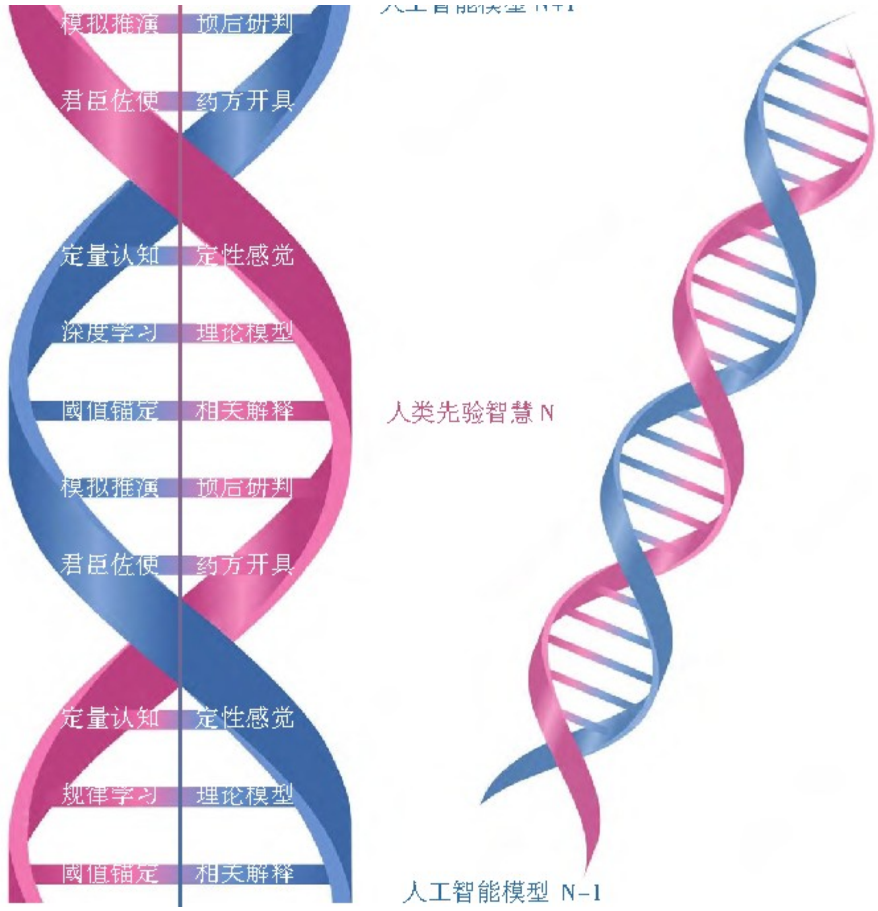

Fig. 1 Theoretical paradigm and model architecture for AI-assisted territorial spatial diagnosis.

Specifically, intelligent territorial spatial diagnosis takes territorial space as a complex living body as its guiding idea and the objective laws of territorial spatial development and evolution as its fundamental basis. It gives full play to the respective strengths of human prior wisdom and AI models in the five main stages of feeling perception, evidence learning, explanatory inference, prognostic judgment and prescription making. Through spiraling hybrid enhancement, it identifies the normal and healthy state in which forms and flows mutually constitute one another, the degree and causes of deviation from this state, and the pain points that seriously deviate from objective laws. It then allocates limited resources to those pain points, thereby pursuing the unity of natural and built environments, the harmony among multiple system elements, and the sustainability of civilizational continuity and innovation.

3.3 General Model Architecture for AI-assisted Territorial Spatial Diagnosis

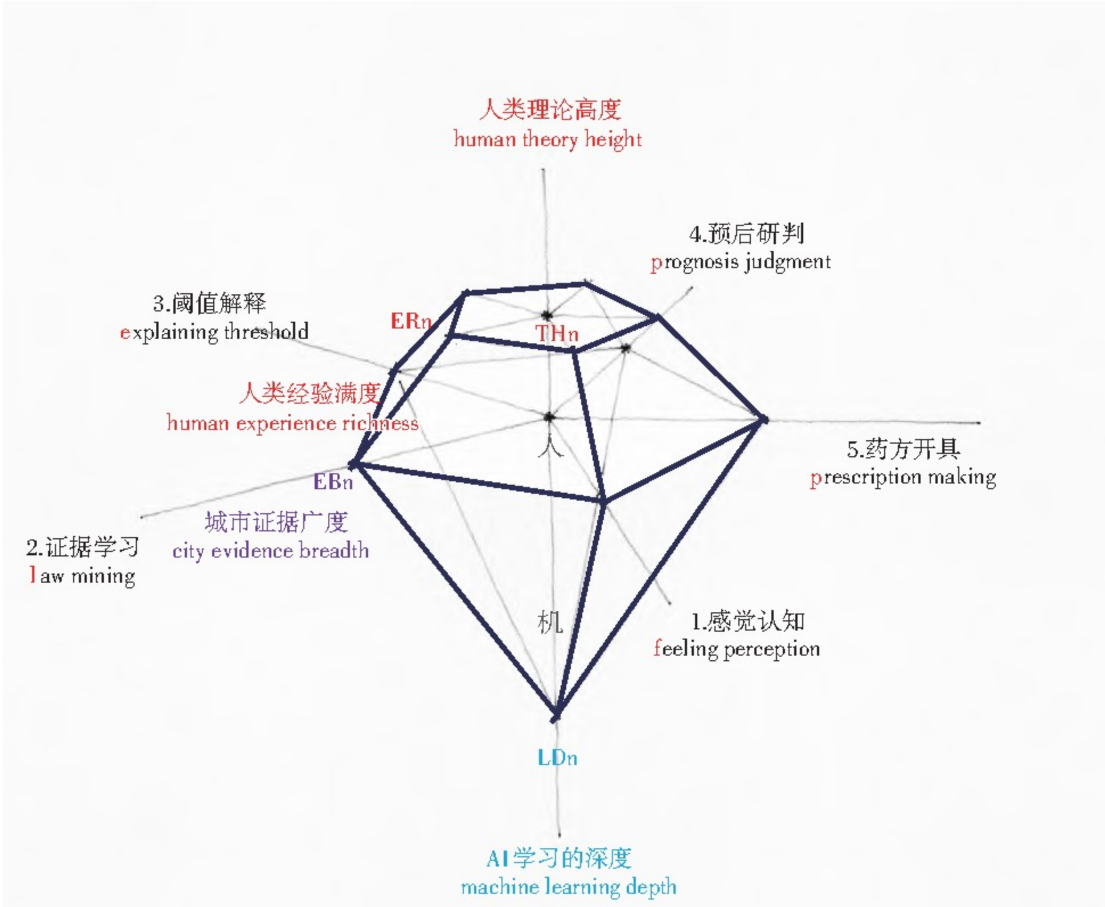

Fig. 2 General model architecture for AI-assisted territorial spatial diagnosis.

Based on the Dual-Helix paradigm of intelligent territorial spatial diagnosis, this study embeds human prior wisdom and AI models into the five main stages of territorial spatial diagnosis and constructs a human-in-the-loop Diamond model for hybrid enhanced intelligent diagnosis. As shown in Fig. 2, the model consists of a pentagonal frustum representing human prior wisdom and a pentagonal pyramid representing AI models. Their combined volume indicates the overall performance of the hybrid enhanced intelligent diagnostic model for territorial space.

4 Changes in Cognitive and Action Methods after Introducing AI into Territorial Spatial Diagnosis

4.1 From One-way Passivity to Collective Initiative

The one-way passive thinking method contains two meanings. First, the one-way treatment of head pain by treating the head and foot pain by treating the foot denies the influence of other systems outside the system and discusses the system only within itself [46]. Second, passivity means that diagnosis often relies on personal will, habits, experience and preferences, and treats routinized and formalized status analysis as territorial spatial diagnosis. Such diagnosis often ends hastily and becomes analysis for its own sake [8].

After AI intervention, the thinking method of territorial spatial diagnosis moves toward collective initiative. Compared with a one-way mode, a collective mode requires both multi-system thinking paths and coordination among them. Compared with passivity, initiative relies on AI's capacities for multi-source perception, deep learning, rigorous reasoning, sensitive feedback and decision support to carry out active health examination of territorial spatial development-stage characteristics and planning implementation effects [47]. Spatial diagnosis is therefore regarded as a task as important as spatial planning.

4.2 From Form-determined Flow to the Mutual Formation of Forms and Flows

The form-determined-flow thinking method takes physical spatial form as the main diagnostic object, regards flows as appendages of physical form and pays limited attention to flows themselves. The mutual formation of forms and flows regards flows in territorial space as the origin of forms. If a form does not conform to the demand laws of flows, flows become blocked and the health of territorial space is affected. Territorial spatial diagnosis should therefore diagnose the health state of flows and judge whether forms conform to the demand laws of flows, so that forms can better follow flows and ensure smooth circulation [1].

4.3 From Experience-oriented Diagnosis to Law-oriented Diagnosis

Experience-oriented diagnosis has two characteristics. First, it is linear. Traditional territorial spatial diagnosis is often based on past experience and relies on linear reasoning paths, making it difficult to adapt to the nonlinear complexity of territorial space. Second, it is rigid. Traditional diagnosis tends to expect results that conform to existing knowledge and experience, and therefore carries inherent subjectivity.

After AI is introduced into territorial spatial diagnosis, the thinking method changes toward law-oriented diagnosis in two ways. First, the habit of random sampling and fragmented experience summarization based on personal will is overturned and replaced by the revelation of territorial spatial development and evolution laws and the diagnosis of deviations from those laws. Second, the simple use of high or low data values as good or bad evaluation standards is replaced by the pharmacological concept of effective dose. This clarifies the minimum effective dose and maximum tolerated dose for law correction and allocates limited resources to pain points with serious deviations from laws.

4.4 From State Diagnosis to Prognostic Diagnosis

State diagnosis refers to the use of certain analytical and examination methods to understand and evaluate the operating state and development condition of a specific territorial space, discover problems and identify their causes. It includes diagnosis of historical and current states [1].

A classical view holds that good governance treats illness before it appears and disorder before it occurs. In medicine, prognosis is used to predict the likely or expected development of disease, including whether signs and symptoms will improve, worsen or remain stable over time, and the possibility of complications and related health problems [48]. Territorial spatial diagnosis faces a similar requirement. It cannot know only the recent past without understanding the future. Prognosis is therefore an urgent need and a key technical difficulty in planning. AI technology can simulate and predict the possible future states and potential problems of territorial space on the basis of its objective laws of development and evolution. It may help resolve problems before they occur and shift territorial spatial diagnosis from state diagnosis toward prognostic diagnosis.

4.5 From Human-machine Separation to Human-machine Collaborative Intelligence

Human-machine separation also contains two meanings. First, territorial spatial diagnosis relies completely on human prior knowledge, and subjective selection is used to choose cases and data that verify past experience and preset spatial problems. Second, diagnosis relies completely on AI models. At present, AI models remain methodologically incomplete for territorial spatial diagnosis and depend heavily on past similar experience and human annotation. Their simulated intelligence often achieves only local rather than global generalization, and their capacity to resist interference under changing conditions is limited [49].

Territorial spatial diagnosis should therefore integrate human prior knowledge and AI models and move toward human-machine collaborative intelligence. This is expressed through human-machine hybrid enhancement, spiral improvement and iterative symbiosis. Humans possess strong theoretical construction capacity and inductive judgment for territorial spatial disorders, while AI can quantitatively reveal the objective laws of territorial spatial development and evolution, determine deviation states, degrees and key causes, and, from the perspective of compound prescriptions, forecast the position of key factors and their combined effects in a prescription so as to formulate a coordinated treatment plan.

5 Systems for Enhancing Working Methods in AI-assisted Territorial Spatial Diagnosis

进行国土空间诊断，主观挑选能够验证 府、企业、市民等多方利益相关者的需

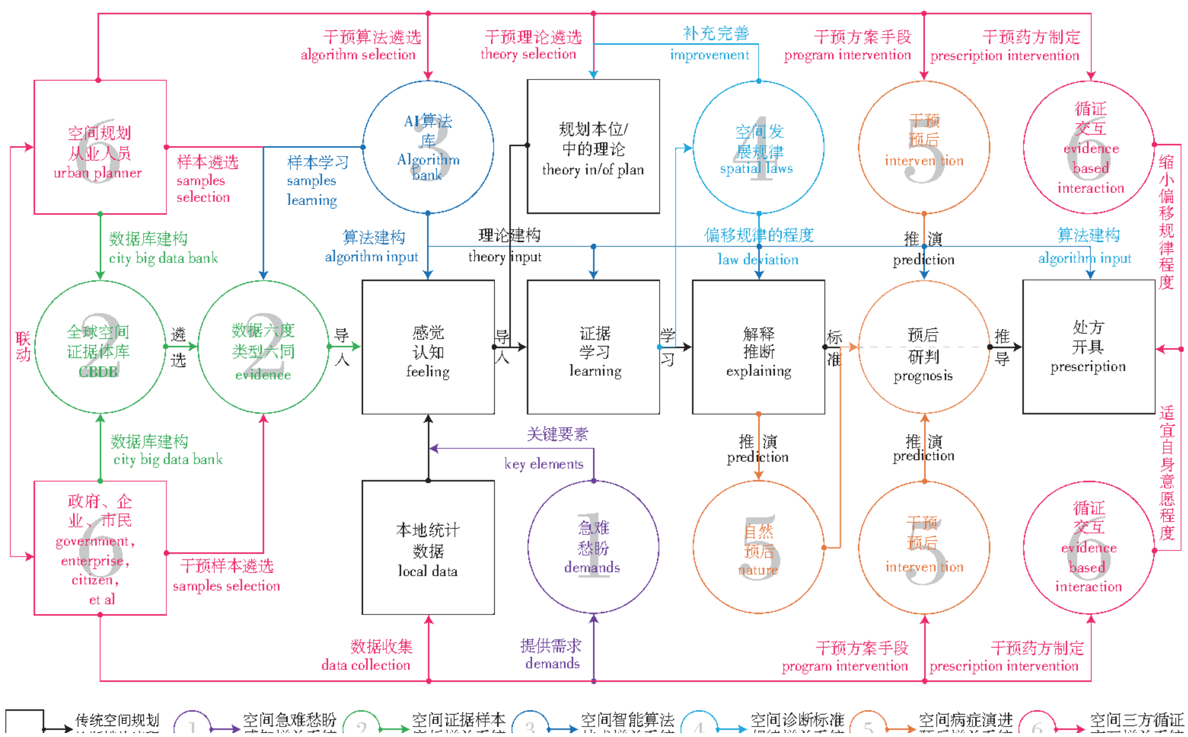

Fig. 3 Six systems for enhancing working methods in AI-assisted territorial spatial diagnosis.

In traditional territorial spatial diagnosis, the basic workflow is to input static and low-frequency panel data, conduct evidence learning through a specific calculation procedure, and then judge territorial spatial problems. In response to the shortcomings of this process, AI-assisted territorial spatial diagnosis will include six systems for enhancing working methods (Fig. 3), which have already been applied effectively in several territorial spatial diagnostic projects in China.

5.1 Perception Enhancement System for Urgent Spatial Needs

Traditional territorial spatial diagnosis usually understands the urgent concerns of multiple stakeholders through interviews and manual classification and summarization. In practice, however, the narrative centers of these sources are often different. The introduction of AI technology makes it possible to perceive the needs of governments, enterprises, citizens and other stakeholders more comprehensively and efficiently from massive cross-media data, including images, texts, videos and audio.

5.2 Baseline Enhancement System for Spatial Evidence Samples

A global spatial evidence sample bank has the characteristics of six data dimensions and six type similarities. The six data dimensions refer to the continuous improvement and expansion of the dimension, breadth, span, granularity, frequency and speed of multi-source heterogeneous data. These improvements make it possible to reveal the laws of territorial spatial development and evolution more accurately and to build a large-scale global territorial spatial evidence sample bank.

The six type similarities refer to similarity in regional space, terrain space, scale space, morphological space, property space and stage space [10]. Clinical medicine often shows major differences between adults and children, men and women, and young and elderly people. Similarly, territorial space is a complex living body. Its gestation, birth, development, mutation, renewal, decline and evolution are not only physical movements from simple to complex, disorder to order and lower to higher levels. They also show different life characteristics according to region, terrain, scale, morphology, property and stage. Typological study of similar life characteristics is therefore a key premise for scientifically establishing reference standards for territorial spatial diagnosis [50].

5.3 Technical Enhancement System for Spatial Intelligence Algorithms

In territorial spatial diagnosis, AI algorithms can be reorganized around five levels, namely feeling perception, evidence learning, explanatory inference, prognostic judgment and prescription making, forming a FLEPP algorithm enhancement system.

Level 1 requires AI algorithms to perceive the development-stage characteristics of territorial space and the implementation effects of planning. Examples include data augmentation algorithms such as variational autoencoders and diffusion models, and dimensionality-reduction algorithms such as autoencoders and convolutional neural networks. Level 2 requires AI algorithms to learn the objective laws of territorial spatial development and evolution, using methods such as spectral clustering, gradient boosting machines, Bayesian learning and neural networks. Level 3 requires AI algorithms to determine the degree of deviation from objective laws and infer the causes of deviation, using global model-agnostic algorithms such as partial dependence plots and local model-agnostic algorithms such as SHAP to identify important features and explain threshold effects.

Level 4 requires AI algorithms to judge short- and long-term effects after spatial self-recovery or intervention, including recovery or progression. Decision-tree learning, neural networks and generative adversarial networks can be used for simulation and prediction. Level 5 requires AI algorithms to supplement and revise spatial self-recovery or planning intervention. Reinforcement learning based on value functions or policy gradients, including actor-critic frameworks, can be used to determine the optimal portfolio of territorial spatial planning strategies.

5.4 Law-based Enhancement System for Spatial Diagnostic Standards

AI technology has the characteristics of system association, deep thinking and ecological thinking. It can mine the evolutionary laws of territorial spatial development through deep learning and formulate diagnostic standards on that basis. Territorial space covers regional linkage, ecological environment, economic industry, science and innovation dynamics, social population, historical culture, transport flows, morphology and function, and health, recreation and sustainability [51-52]. It implements the ideas of unity between humans and nature, system harmony and intergenerational sustainability, and responds to three key disorders: lack of fit, namely conflict between natural and built environments; lack of harmony, namely imbalance among multiple system elements; and lack of continuity, namely disconnection between civilizational continuation and innovation [10]. These ideas form the HOS law enhancement system for territorial spatial diagnosis.

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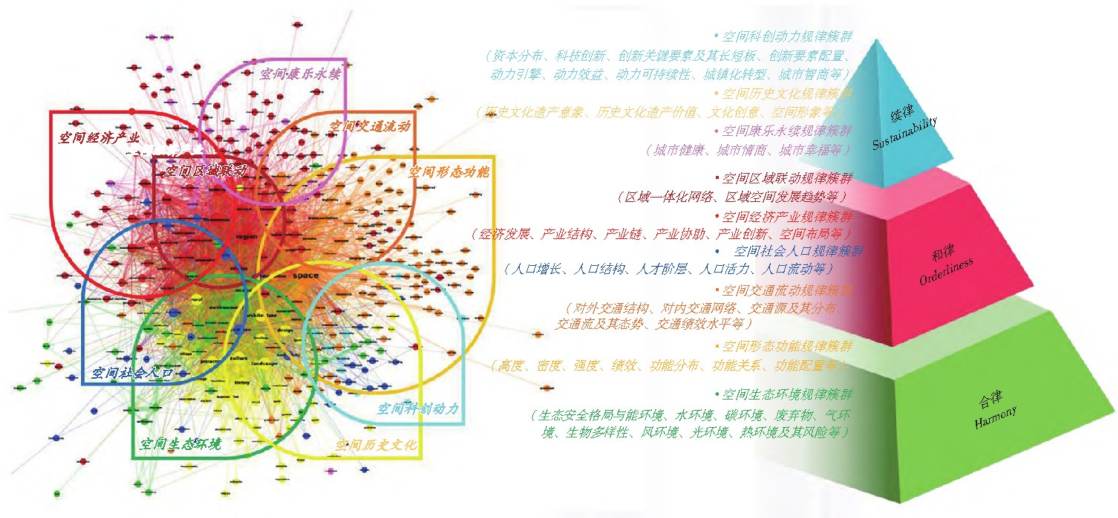

图4 国土空间智能诊断的“HOS”规律增益系统

Fig.4 The "HOS" law gain system of AI—assisted territorial spatial diagnosis

Fig. 4 HOS law enhancement system for AI-assisted territorial spatial diagnosis.

(1) The spatial law of fit includes the cluster of spatial ecological-environmental laws. (2) The spatial law of harmony includes clusters of laws for spatial economic industry, spatial social population, spatial transport flows, spatial morphology and function, and spatial regional linkage. (3) The spatial law of continuity includes clusters of laws for spatial science and innovation dynamics, spatial historical culture, and spatial health, recreation and sustainability.

5.5 Prognostic Enhancement System for the Evolution of Spatial Disorders

In medicine, prognosis refers to the experience-based prediction of disease development. It can be divided into natural prognosis and intervention prognosis, which respectively predict the development process and consequences of a disease with or without medical treatment or intervention.

Similarly, territorial spatial diagnosis after the introduction of AI adds a prognostic enhancement system for the evolution of spatial disorders. It can also be divided into natural prognosis and intervention prognosis. Under conditions with or without planning intervention, this system simulates and predicts the development process and consequences of a particular territorial spatial disorder on the basis of the objective laws of territorial spatial development and evolution [53].

The prognostic enhancement system should pay particular attention to the resilience mechanism of territorial space. If the mechanism has a positive effect, planning should work with it; if it has a negative effect, planning should improve it against the trend [13]. Respecting the self-recovery laws of territorial space will reduce planning costs, which is also one of the foundations of territorial spatial diagnosis.

5.6 Interactive Enhancement System for Tripartite Evidence

Intelligent territorial spatial diagnosis adds a tripartite interaction enhancement system based on the objective laws of territorial spatial development and evolution, the practical experience of spatial planning practitioners and the urgent concerns of multiple stakeholders. It collaboratively formulates diagnostic methods and treatment plans for territorial spatial disorders, thereby achieving optimal diagnostic and treatment effects. Tripartite evidence-based interaction is mainly reflected in six aspects.

(1) Spatial planning practitioners and multiple stakeholders can intervene in the selection of the spatial evidence sample reference system according to the six type similarities of space. (2) They can intervene in the construction of diagnostic theoretical models according to the theory of planning (TOP) and theory in planning (TIP). (3) They can intervene in the selection of diagnostic technical models according to the accuracy, efficiency, robustness, interpretability and generalization capability of different AI algorithms.

(4) The laws of territorial spatial development and evolution based on the global spatial evidence sample bank further improve TOP and TIP and further enhance the practical experience of spatial planning practitioners. (5) Spatial planning practitioners and multiple stakeholders can intervene in spatial planning schemes and simulate the process and consequences of territorial spatial disorders. (6) Following the principles of minimizing the degree of deviation from laws and maximizing suitability to stakeholder preferences, spatial planning practitioners and multiple stakeholders jointly formulate prevention and treatment plans for territorial spatial disorders in a coordinated prescription logic.

6 Conclusion

Promoting the deep integration of AI technology and territorial spatial diagnosis is an urgent need for enhancing the theoretical characteristics of territorial spatial diagnosis oriented toward objective laws, multiple coordination, temporal evolution and the mutual formation of forms and flows. Guided by the idea that territorial space is a complex living body and grounded in the objective laws of territorial spatial development and evolution, this study constructs the Dual-Helix paradigm and Diamond architecture for territorial spatial diagnosis after the introduction of AI technology from the perspectives of principles, theory and models.

On this basis, the study explains five directions of change in thinking methods after AI is introduced into territorial spatial diagnosis: from one-way passivity to collective initiative, from form-determined flow to the mutual formation of forms and flows, from experience orientation to law orientation, from state diagnosis to prognostic diagnosis, and from human-machine separation to human-machine collaborative intelligence. It further proposes six systems for enhancing working methods, namely the perception of urgent concerns, the baseline of evidence samples, the technology of intelligent algorithms, the laws of diagnostic standards, the prognosis of disorder evolution and tripartite evidence-based interaction. These systems are expected to address the problems and symptoms of traditional territorial spatial diagnosis, further improve the scientific rationality of territorial spatial planning and promote the sustainable development of territorial space.

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Notes

① On one hand, during the practice of the five task stages of territorial spatial diagnosis, practitioners can continuously conduct human-brain learning of evidence bodies (EBn), thereby improving the theoretical height (THn) and experiential richness (ERn) of territorial spatial diagnosis. In general, an individual's experiential richness does not exceed the evidence breadth of the complete set, namely ERn <= EBn, and human prior wisdom is thereby comprehensively strengthened. On the other hand, AI models can continuously conduct machine learning (LDn) from evidence bodies (EBn), improve the application of knowledge obtained from limited evidence to new situations, and comprehensively enhance the generalization capability of the model. Continuous improvement of THn, ERn, EBn and LDn can therefore strengthen the overall performance of the model.

② http://www.wupen.org/lectures/190?lesson=446

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