# Technical Paradigm and Model Construction for Embedding Large Models into Professional Urban Planning Practice

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Abstract: Starting from the connotation of professional work in urban planning and the typology of artificial intelligence, this paper focuses on the technical paradigm through which large models can be embedded into professional urban planning practice and proposes a pathway for constructing professional planning large models. Urban planning practice follows a diagnosis-inference-treatment working mode and uses domain knowledge to provide solutions. By distinguishing perceptual intelligence from cognitive intelligence, the paper argues that large models can support this working mode. It further proposes a technical framework in which professional planning large models acquire domain knowledge through diagnostic training and treatment training. An empirical case shows that professional planning large models can acquire the planning capabilities of identifying spatial problems, inferring their causes and proposing planning strategies. The findings indicate that the technical paradigm for embedding large models into urban planning practice is based on professional large models equipped with both general knowledge and domain knowledge, and that it supports problem-oriented and law-oriented planning paradigms through the diagnosis-inference-treatment working mode. Professional planning large models are the carrier of this paradigm. Their construction centers on domain knowledge and is realized through diagnostic training and treatment training on the basis of general large models. Domain-specific professional large models can be effectively embedded into planning practice and can enhance planners' professional capacity.

Keywords: professional large models; urban planning; domain knowledge; diagnosis-inference-treatment; diagnostic training; treatment training

As a strategic technology leading a new round of global scientific, technological and industrial change, artificial intelligence is profoundly reshaping production and everyday life. Large models have opened a new stage in the development of AI. They are rapidly entering economic sectors, social governance and public services, and they are also penetrating research in the natural and social sciences. Since 2025, large models have begun to enter urban planning research, and their empowerment of planning research and practice has quickly become a shared concern of academia and the profession [1].

Recent studies on large models in urban planning can be divided by technical use into perceptual uses and reasoning uses. Perceptual uses apply large models to perceive the morphological characteristics, functional attributes and underlying socioeconomic phenomena of urban space. They include the perception of street and park-space themes [2], street spatial quality [3], urban spatial safety [4] and poverty-related socioeconomic phenomena [5]. These studies rely on the vision-language understanding of multimodal large models and realize a transformation from images to semantics. Large models can produce spatial perception consistent with that of ordinary citizens [6], which makes them useful for urban spatial evaluation.

Reasoning uses apply large models to the semantic analysis of multimodal information and use this analysis to infer and predict features, demands or feedback related to urban space. Such studies include inferring urban functions from street-view images [7], generating images for urban design and street renewal [8-9], interpreting planning policy documents and analyzing public feedback [10], and predicting human mobility under public events [11]. These studies rely on the reasoning capability of large models and can effectively support analysis and prediction.

From the perspective of use mode, large models can be used in two ways. The first treats a general large model as an ordinary public participant in planning research, simulating public perception and participation. Examples include analyses of public preferences for urban space and landscape [6, 12] and simulations of public participation in planning processes [13]. The second constructs professional planning large models on the basis of general large models, so that large models can perform the role of planning professionals. Such models can generate design intentions and scenarios [8-9], infer land-use categories and the spatial distribution of socioeconomic conditions [14], and predict spatiotemporal travel demand from multi-source data [11, 15]. Existing research has explored both perceptual and reasoning uses of large models in planning. It remains necessary to clarify the relationship and differences between the two technical uses and to identify how AI uses match professional planning work. Existing studies also show that large models can undertake tasks performed by ordinary citizens, such as public participation, and can also undertake professional tasks such as traffic prediction. It is therefore also necessary to distinguish these two use modes and clarify their respective application domains. This paper addresses these two issues from two dimensions: the knowledge structure and spatial planning paradigm of professional planning work, and the stage of AI represented by large models. It proposes a technical paradigm for embedding large models into professional urban planning work and a method for constructing professional large models applicable to planning practice.

## 1 Connotation of Professional Planning Work

### 1.1 Knowledge Structure: General Knowledge plus Domain Knowledge

In cognitive science and educational psychology, knowledge is commonly divided into general knowledge (GK) and domain knowledge (DK) [16]. General knowledge refers to factual and common-sense knowledge that is broadly applicable across disciplines, such as language, history, mathematics, physics and geography. Domain knowledge refers to highly structured and deeply organized professional knowledge within a specific discipline or industry, such as planning principles and urban spatial structure in urban planning. Domain knowledge is formed through continuous learning and practice in a specific field on the basis of general knowledge.

From the perspective of knowledge, professional work essentially uses domain knowledge to solve professional problems and create professional value. Cognitive science shows that the difference between experts and novices lies mainly in the degree to which domain knowledge is mastered, not in general knowledge [17]. This pattern also applies to AI. General large models acquire general knowledge during pretraining, but they do not systematically cover domain knowledge. A study [18] tested a general large model across 556 professional urban planning tasks. It performed well on tasks dominated by general knowledge, such as information retrieval and planning-text assistance, but performed poorly on tasks highly dependent on domain knowledge, such as planning decisions and spatial design.

The difference in knowledge structure explains the two ways in which large models are applied to professional planning work. When a general large model is used as an ordinary public participant in planning research, its general knowledge is being used. This includes simulating public perception and preferences for urban space [4-6] and supporting public expression and participation [13, 19-20]. When a large model is expected to act as a planning professional, it must use both general knowledge and domain knowledge. This includes planning-intention generation [8-9, 21], inference of land use and socioeconomic features [7, 14], and prediction of travel demand [11, 15]. In terms of knowledge structure, the fundamental difference between the two use modes lies in whether the model calls only general knowledge or incorporates domain knowledge.

### 1.2 Spatial Planning Paradigm: The Diagnosis-Inference-Treatment Working Mode

The problem-oriented planning paradigm is an important expression of modern planning thought. With rapid industrialization and large-scale urbanization, spatial problems such as urban diseases emerged in large numbers, requiring planning to construct spatial solutions from concrete problems. Geddes [22] proposed survey before plan and extended the analogy to diagnosis before treatment, emphasizing that investigation and diagnosis of urban operation should support planning decisions. Mumford [23] further stressed first-hand investigation and diagnosis of metropolitan diseases and proposed corresponding planning strategies. Later scholars summarized this paradigm as investigation, evaluation, plan preparation and implementation. These planning ideas all emphasize problem orientation and the formulation of planning strategies in response to specific spatial problems.

On this basis, Wu Zhiqiang et al. [24] proposed a law-oriented planning paradigm, which emphasizes spatial diagnosis, simulation and scenario creation according to the laws of urban development. Under both problem-oriented and law-oriented paradigms, professional planning work follows the logic of identifying spatial problems, inferring their causes and proposing planning strategies. This logic can be summarized as the diagnosis-inference-treatment working mode.

The diagnosis-inference-treatment mode consists of two stages: spatial diagnosis and spatial treatment. Spatial diagnosis absorbs the idea of clinical diagnosis in medicine and uses existing theoretical knowledge and summarized laws to understand and analyze urban problems [25-26]. It corresponds to the process from identifying spatial problems to inferring their causes, and it emphasizes not only diagnostic results but also reasoning about concrete causes. Spatial treatment corresponds to the process from inferring causes to proposing planning strategies, and it also emphasizes the reasoning process before strategies are proposed. The same spatial problem may have different causes in different contexts, and its treatment must therefore be adapted to local conditions. Inference plays a key role in both stages.

In summary, the connotation of professional urban planning work can be described as providing solutions to urban spatial problems through the diagnosis-inference-treatment working mode, supported by a knowledge structure composed of general knowledge and domain knowledge. This connotation forms the basis of the technical paradigm for embedding large models into professional planning work.

## 2 Perceptual Intelligence, Cognitive Intelligence and Professional Planning Work

### 2.1 From Perceptual Intelligence to Cognitive Intelligence

AI development is often divided into stages such as computational intelligence, perceptual intelligence, cognitive intelligence and autonomous intelligence [27]. Most current AI technologies belong to perceptual intelligence. Perceptual intelligence refers to a machine's capacity to acquire and identify perceptual data such as speech, images and videos. Typical tasks include semantic segmentation and object detection through deep learning, and typical capabilities include classification, detection and prediction [28]. In medical image analysis, for example, deep-learning models can detect lesions and output objective observations [29]. Clinical diagnosis, however, still requires doctors to integrate medical history and physical examination and to conduct causal reasoning and risk judgment within the medical knowledge system. Perceptual intelligence cannot complete these latter tasks.

Large models mark a new stage in the development of AI toward cognitive intelligence. Cognitive intelligence emphasizes the machine's capacity to form understanding, reasoning, judgment and explanation on the basis of perceptual information, moving from recognition to understanding. Large models can display multi-step reasoning abilities such as chain of thought and show a degree of quasi-cognitive capacity [30]. Although large models can also produce objective observations, they have stronger technical capacity to move from seeing to subjective analytical reasoning. In medicine, for example, professionally trained medical large models can synthesize patient symptoms and medical history, reason toward diagnosis and even provide treatment plans [31]. Compared with lesion detection by perceptual intelligence, cognitive capacity can connect perceived lesions with professional knowledge structures and support the subjective analytical reasoning processes of medical diagnosis and treatment.

### 2.2 Perceptual Intelligence and Cognitive Intelligence in Urban Planning

Perceptual intelligence has been widely applied in urban planning to identify urban spatial elements and quantify spatial morphology. Over the past decade, deep-learning methods represented by semantic segmentation, object detection and image classification have identified elements such as street green-view index, sky-view exposure and building morphology indices. These methods provide important support for quantitatively understanding urban form and spatial quality [32-33]. However, they can only measure features of urban spatial elements. They cannot infer the causes behind those features or generate optimization strategies according to those causes, and therefore cannot fully support the diagnosis-inference-treatment working mode.

The core difference between the two current technical uses of large models in urban planning lies in their different emphasis on perceptual and cognitive capabilities. Perceptual uses belong to perceptual intelligence. They rely on multimodal perception to expand the recognition boundary and application scenarios of traditional deep learning, including natural-language description and spatial-quality evaluation of street-view images [2, 34], comparison of changes in urban environments [35], and subjective perception of socioeconomic phenomena [4-5]. The text-perception capability of large models has also been applied to policy analysis, public-opinion interpretation and geographic semantic modeling [12, 19, 36]. These uses do not move beyond the core scope of traditional deep learning and still belong to perceptual intelligence.

Reasoning uses belong to cognitive intelligence. They use large models to perform professional planning tasks such as spatial diagnosis, causal reasoning and strategy generation on the basis of perceived elements and features. Under the condition of incorporating planning domain knowledge, large models can infer urban and building functions [7, 14], generate planning and design intention images [8-9, 21], professionally interpret planning policy documents [10], and predict transport demand under special public events [11]. Although these studies complete only parts of the full diagnosis-inference-treatment process, they already show that large models have potential for spatial diagnosis and spatial treatment in professional planning work.

Compared with AI technologies at the stage of perceptual intelligence, the key potential of large models lies in their cognitive intelligence. They can infer causes from perceived phenomena and generate optimization strategies according to those causes. This makes it technically feasible for large models to support the complete diagnosis-inference-treatment working mode and provides the technical basis for embedding them into professional urban planning work.

## 3 Technical Paradigm and Model Framework

### 3.1 Technical Paradigm for Embedding Large Models into Professional Urban Planning Work

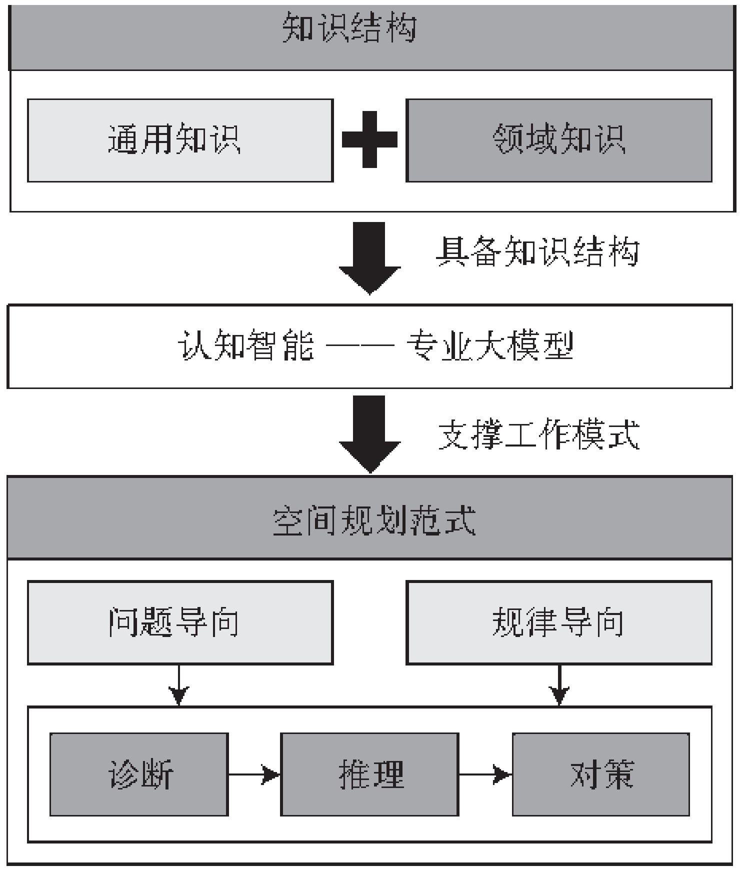



**图1　大模型融入城市规划专业工作的技术范式**

Fig.1　Technical paradigm for embedding large mod-els into urban planning practice

Fig. 1 Technical paradigm for embedding large models into professional urban planning practice.

The technical paradigm for embedding large models into professional urban planning work uses professional large models with a knowledge structure of general knowledge plus domain knowledge to support the full diagnosis-inference-treatment process and the problem-oriented and law-oriented planning paradigms (Fig. 1). Professional planning large models are the technical carrier of this paradigm.

The feasibility of this paradigm comes from the fit between the requirements of the spatial planning paradigm and the technical strengths of large models. The core of the problem-oriented planning paradigm is to diagnose urban spatial problems through data analysis, infer causes with planning domain knowledge, and propose corresponding spatial planning strategies. Large models are a representative advance in cognitive intelligence and possess multi-step reasoning capability. By introducing planning domain knowledge into general large models and constructing professional planning large models, the diagnosis-inference-treatment working mode can be technically supported.

This paradigm is particularly necessary in the era of stock-space planning. In response to the need to renew and improve existing urban space, traditional planning technologies face challenges of scale and refinement. Scale refers to the large amount of urban space requiring renewal; refinement refers to the need to identify spatial problems precisely and propose differentiated strategies. Professional planning large models can diagnose existing spaces at large scale by relying on domain knowledge and can infer differentiated planning strategies. Their advantages in scalable processing and stability can compensate for the limitations of traditional planning technologies.

### 3.2 Construction of Professional Planning Large Models

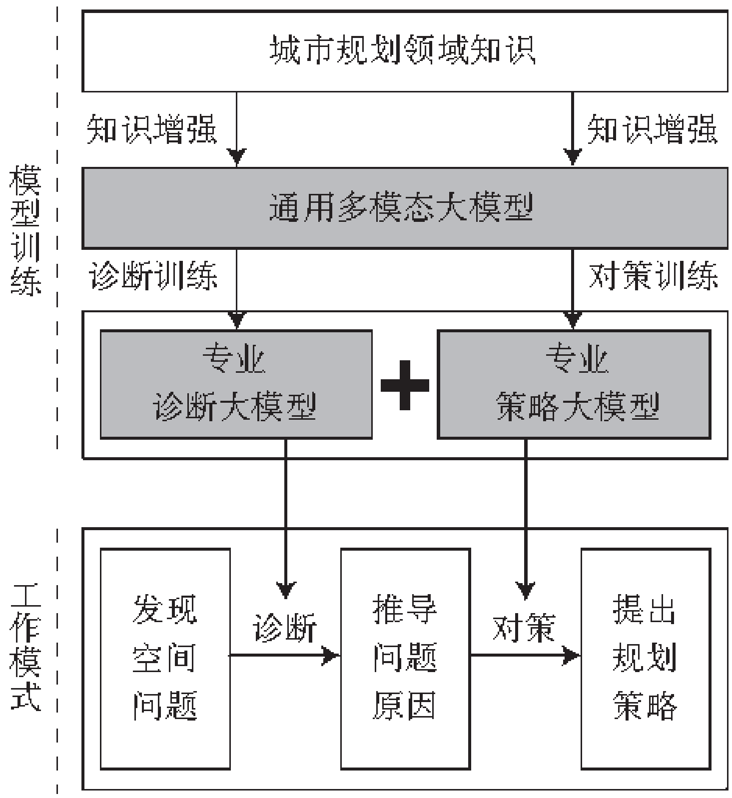



图2 构建规划专业大模型的技术框架

Fig.2 Technical framework for constructing profes-

Fig. 2 Technical framework for constructing professional planning large models.

The key to implementing the technical paradigm lies in constructing professional planning large models. The technical framework for constructing such models to support the diagnosis-inference-treatment working mode is shown in Fig. 2.

Professional planning large models are constructed around the logic of identifying spatial problems, inferring their causes and proposing planning strategies. Planning domain knowledge is divided into diagnostic domain knowledge and treatment domain knowledge, which are separately integrated into a general large model. Diagnostic domain knowledge supports professional judgment in identifying spatial problems and inferring their causes, with emphasis on spatial-state recognition, problem diagnosis and causal analysis. Treatment domain knowledge supports professional reasoning from causes to planning strategies, with emphasis on planning intervention logic, strategy selection and spatial response.

These two types of domain knowledge are learned through diagnostic training and treatment training. The objective is to enable the model to master the domain knowledge required in the spatial diagnosis and spatial treatment stages. Both stages can be realized through knowledge-enhancement methods such as fine-tuning and prompt engineering. Learning these two types of domain knowledge addresses the shortage of domain knowledge in general large models and supports the full diagnosis-inference-treatment working mode.

### 3.3 Application Positioning of Professional Planning Large Models

The appropriate application positioning of professional planning large models is that of professional planning assistants. Their diagnostic and treatment outputs should be used as references for decision-making. Planning professionals still play the leading role, including evaluating diagnostic results, assessing the quality of strategies and making final decisions. Core humanistic attributes of planning, such as value judgment and balancing public interests, cannot necessarily be fully contained in domain-knowledge training. Large models have technical advantages in efficiently processing massive data. They can undertake large-scale preliminary diagnosis, propose reference schemes for decisions and provide evidence-based support. The nature of professional planning work and the technical characteristics of large models jointly determine this assistant role.

## 4 Empirical Case

### 4.1 Case Selection

Under the principle of conducting health examination before renewal and not renewing without examination, megacities and large cities face urgent demands for large-scale and dynamic urban health examination and renewal. Within Shanghai's Inner Ring, an area of about 120 km2 contains 1,326 streets and roughly 5,300 street segments defined by road intersections. These street spaces all face the need for renewal and quality improvement. Embedding large models into professional work for stock-space renewal can support large-scale diagnosis of spatial problems and differentiated planning strategies.

This study uses the improvement of street walking safety in street-space renewal as an empirical case. It constructs a professional large model to support the process of identifying spatial problems, inferring problem causes and proposing planning strategies in street-space renewal, thereby verifying the technical paradigm and model-construction method proposed in this paper.

### 4.2 Model Training

#### 4.2.1 Domain Knowledge Structure for Street Walking Safety

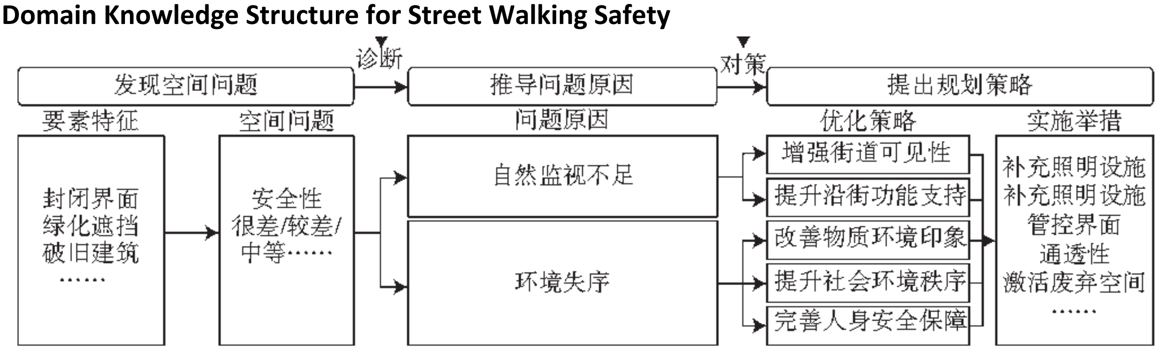



图3 街道步行安全性诊断—对策的训练框架

Fig.3 Training framework for diagnosis – treatment reasoning in street walking safety

Fig. 3 Training framework for diagnosis-treatment reasoning in street walking safety.

Improving street walking safety is a typical professional urban planning task. To construct a professional large model for street walking safety, diagnostic domain knowledge and treatment domain knowledge are first sorted

and distinguished (Fig. 3), so as to support the two-stage model training of diagnostic training and treatment training.
Diagnostic domain knowledge is based on Alfonzo's hierarchy of walking needs [37]. This theory includes a safety level and classifies the causes of poor street safety into insufficient natural surveillance and environmental disorder. Insufficient natural surveillance refers to walking environments that lack opportunities for observation and intervention, which amplifies pedestrians' perceived risk of hidden crime and suppresses walking willingness. Environmental disorder refers to physical decline in walking environments, such as damage, mess and abandonment, which causes pedestrians to overestimate safety risks and avoid using the space. These two categories of causes support diagnostic reasoning from identifying spatial problems to inferring their causes and connect with the spatial diagnosis stage.
Treatment domain knowledge is based on crime prevention through environmental design (CPTED) theory [38], which proposes multiple optimization strategies for the two categories of causes above. Taking insufficient natural surveillance as an example, responses can be summarized as enhancing street visibility and strengthening functional support along the street, thereby supporting the spatial realization of eyes on the street from the perspectives of being visible and being watched. This treatment knowledge provides the professional basis for reasoning from causes to planning strategies after diagnostic results have been obtained, and connects with the spatial treatment stage.

#### 4.2.2 Domain Knowledge Training for Street Walking Safety

Using the general multimodal large model Qwen3-VL-32B as the base model, this study constructs a professional large model for street walking safety through domain-knowledge training. Because diagnostic domain knowledge and treatment domain knowledge differ in nature, two distinct knowledge-enhancement paths are adopted in diagnostic training and treatment training.
Diagnostic training enables the professional large model to master knowledge about street walking safety in the hierarchy of walking needs through low-rank adaptation (LoRA) fine-tuning [39]. Although the hierarchy of walking needs has a clear conceptual system and causal logic, the perception of real street space involves intertwined effects of many spatial elements. It is tacit knowledge and is difficult to express through explicit rules [8]. LoRA fine-tuning is therefore used to train the general large model and is suitable for learning tacit knowledge. The training samples consist of street-view images and diagnostic texts. The diagnostic texts rate street walking safety, identify the main causes according to the hierarchy of walking needs, and describe the corresponding spatial features in natural language.

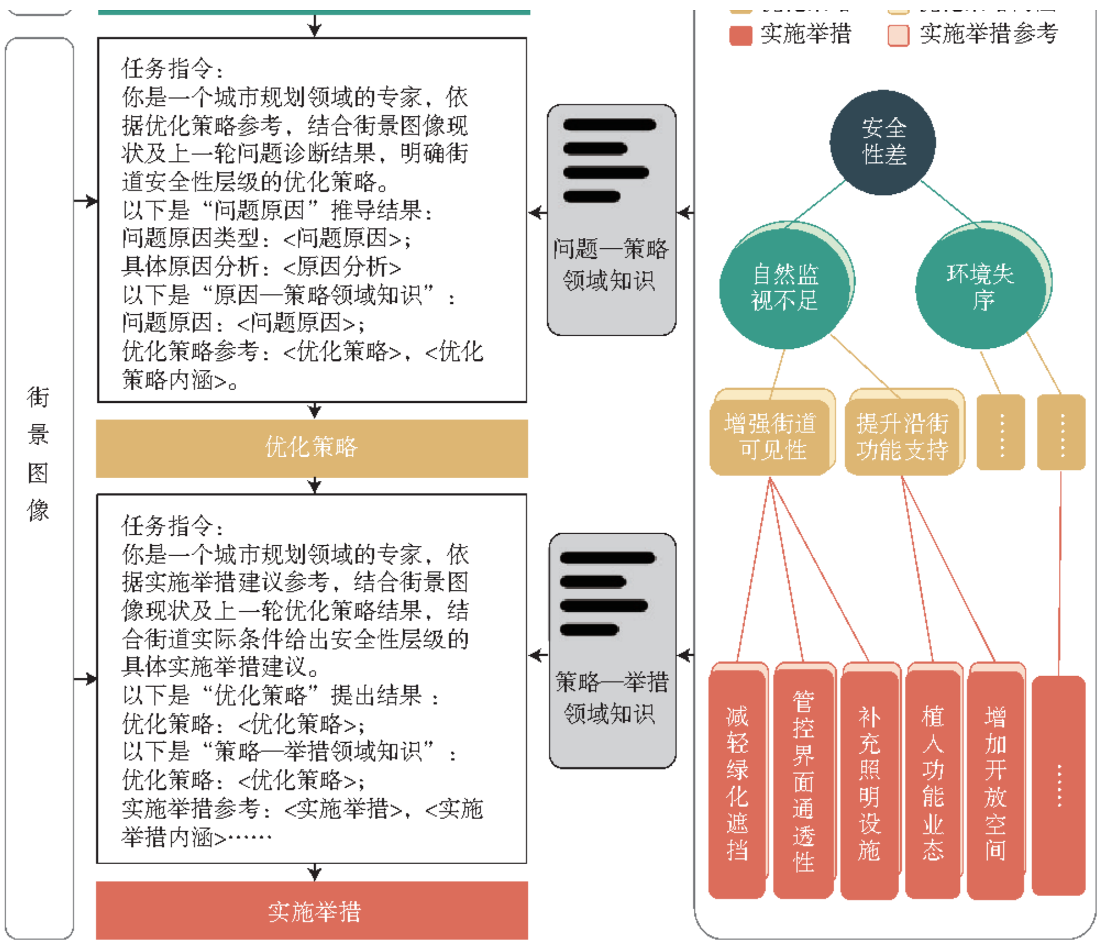



图4　基于“街景图像+诊断文本+对策领域知识”的对策训练提示词设计

Fig.4　Prompt design for treatment training based on "SVI + diagnostic text + treatment domain knowledge"

表1　专业大模型的典型街道诊断输出结果

Tab.1　Outputs of diagnosis reasoning for a typical street segment generated by the professional large models

Fig. 4 Prompt design for treatment training based on street-view imagery, diagnostic text and treatment domain knowledge.

Treatment training enables the professional large model to master CPTED-based treatment knowledge for street walking safety through prompt engineering. CPTED-based treatment knowledge has a clearer problem cause-planning strategy structure, in which the same cause can correspond directly to several optimization strategies and specific measures can be selected according to actual street conditions. It is therefore suitable to explicitly introduce structured treatment knowledge during reasoning, enabling on-demand use and dynamic adaptation. The treatment-training prompt consists of task instructions, diagnostic text and treatment domain knowledge (Fig. 4). Task instructions clarify the model's professional reasoning objective. Diagnostic text from the previous step provides comprehensive and concrete spatial-background information through identified causes. Structured treatment domain knowledge systematically explains the logical relationships among different causes, optimization strategies and implementation measures.

Through diagnostic training and treatment training, the professional large model for street walking safety learns the hierarchy of walking needs and CPTED theory. For each input street-view image, it can provide a street-safety diagnosis in natural language, infer causes, and further propose optimization strategies and implementation measures for improving walking safety.

### 4.3 Model Application

#### 4.3.1 Diagnosis and Treatment for a Typical Street Segment

| 诊断 | 专业大模型的输出结果 | 通用大模型的输出结果 |
|---|---|---|
| 发现空间问题 | 该街道步行安全性较差 | 该街道人行道被大量共享单车侵占，迫使行人进入车行道，增加碰撞风险；步行空间连续性中断，影响通行安全与应急疏散；右侧建筑立面老旧破损，环境杂乱，引发心理不安与犯罪感知；两侧树木过密，夜间或阴雨天易造成视线遮蔽，形成安全隐患。这些问题相互叠加，削弱了步行者的物理安全与心理安全感，故该街道步行安全性评价为“较差” |
| 推导问题原因 | 问题原因为自然监视不足。具体表现为街道右侧存在封闭界面，造成视线通透性差，缺乏有效的自然监视；同时，未见路灯、监控、商铺等安全支持要素，也无明显日常活动，导致环境缺乏活力与心理安全感支撑。上述因素共同削弱了步行者对街道安全性的感知，构成明显的自然监视不足问题。环境失序方面，未见破败建筑、杂乱街道、垃圾或施工行为等要素，故不构成环境失序问题 | |

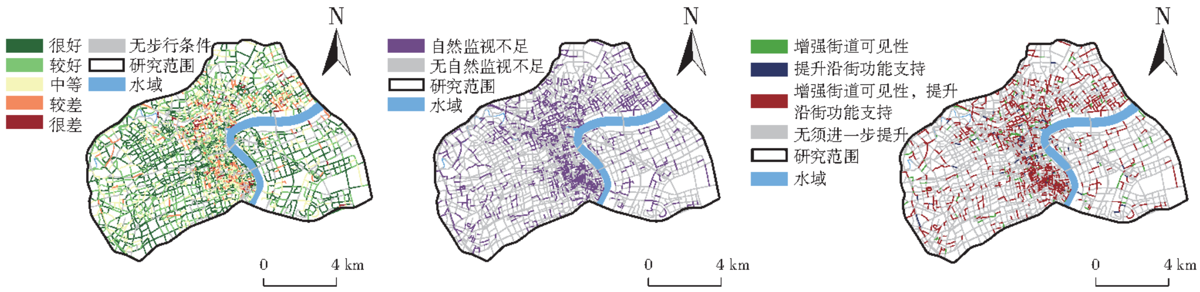
25

Tab. 1 Outputs of diagnosis reasoning for a typical street segment generated by professional large models.

To verify the feasibility and effectiveness of the framework for constructing professional planning large models, a typical street-section case is selected. The diagnostic outputs generated by the two-stage trained professional large model are compared with those of an untrained general large model (Table 1).

The results show that the trained professional large model can strictly follow the street-safety knowledge in the hierarchy of walking needs when conducting diagnostic reasoning. It clearly identifies insufficient natural surveillance as the core cause of poor walking safety on the street, and provides interpretable professional attribution by combining spatial interface form and street activity characteristics. On this basis, according to CPTED theory, it proposes intervention directions and implementable measures in spatial optimization, including improving functional support along the street and enhancing street visibility. The untrained general large model can accurately perceive elements of the walking environment, but its diagnosis remains at the level of surface problems such as shared bicycle disorder, old interfaces and insufficient lighting. It does not conduct professional reasoning based on street-safety knowledge in the hierarchy of walking needs. Its treatment output is also a recommendation for urban operation management rather than spatial optimization. This empirical result verifies the effectiveness of the proposed technical paradigm at the application level.

#### 4.3.2 Diagnosis and Treatment for All Street Segments




（a）空间问题发现　（b）问题原因推导（以自然监视不足为例）　（c）规划策略提出（以自然监视不足为例）

**图 5　上海内环内城区的街道步行安全性诊断和策略**

Fig.5　Diagnosis and treatment for walking safety across streets within Shanghai's Inner Ring

4.3.2　全部街道步行安全性诊断与对策

专业大模型能够在 1 h 内完成上海内环以内全部 5300 个街段的空间诊断与策略推演[②]。结果显示，上海内环以内街道

理任务。进一步分析专业大模型与专业人员共识不一致的案例发现：专业大模型未出现诊断问题"漏报"现象；差异仅源于存在极少量的"误报"。这意味着

验依赖。相比之下，专业大模型展现出更高的稳定性，能够持续输出接近专业人员平均水平的策略建议，为专业规划师提供可参考策略建议。

Fig. 5 Diagnosis and treatment for walking safety across streets within Shanghai's Inner Ring.

The professional large model can complete spatial diagnosis and strategy simulation for all 5,300 street segments within Shanghai's Inner Ring in one hour. The results show that walking safety is generally good: 65.47% of streets are rated as very good or good [Fig. 5(a)]. For the 34.53% of street segments rated medium or below, the model further diagnoses two main causes: insufficient natural surveillance [Fig. 5(b)] and environmental disorder. In response to the negative effects of insufficient natural surveillance, it proposes differentiated spatial optimization strategies [Fig. 5(c)] and recommends implementation measures for each street segment. This case shows that professional large models can conduct rapid large-scale diagnosis and propose differentiated planning strategies, and that they can undertake large-scale and routine professional renewal examination for stock urban space.

**4.4 Model Evaluation**


**图 6　"诊断—推理—对策"专业大模型与专业人员的比较**

tween the "diagnosis—inference—treatment" professional large model and human professionals

Fig. 6 Comparison between the diagnosis-inference-treatment professional large model and human professionals.

To verify the reliability of the professional large model for street walkability in cognitive reasoning, thirteen professionals with complete urban-planning education backgrounds were invited to participate in model evaluation. A test set was composed of 52 randomly selected street-view images. Accuracy and F1-score were used to compare the professional large model, the general large model and human professionals in the stages of spatial diagnosis and spatial treatment (Fig. 6).

The evaluation results show that, in inferring problem causes, the professional large model achieves an accuracy score of 0.88, differing from the average level of professionals (0.94) only within a two-standard-deviation interval. This indicates that its capability falls within the normal fluctuation range of the professional group. By contrast, the general large model achieves an accuracy of only 0.61, which is significantly lower than the professional average and insufficient for professional reasoning tasks.

Further analysis of cases where the professional large model differs from professional consensus shows that the model does not miss diagnostic problems; discrepancies mainly arise from a very small number of false positives. This means that the professional large model is especially suitable for early warning in urban renewal. It can diagnose potential problem spaces at large scale and automatically, helping professionals quickly identify objects requiring further judgment and thereby forming an efficient workflow of early warning before confirmation.

In proposing planning strategies, the professional large model is broadly comparable to professionals. The differences in accuracy and F1-score are both only about 0.1. Notably, individual differences among professionals increase significantly in the strategy stage compared with diagnostic reasoning, reflecting stronger subjective preferences and experience dependence in selecting spatial optimization schemes. By contrast, the professional large model shows greater stability and can continuously output strategy suggestions close to the average professional level, providing reference strategies for planners.

The evaluation confirms that the proposed technical paradigm can reliably support professional planning work. The professional large model constructed in this case is suitable for implementing the diagnosis-inference-treatment workflow at large scale and with stability in the context of stock-space renewal, and its capability meets the application positioning of a professional planning assistant.

## 5 Conclusions and Discussion

### 5.1 Conclusions

From the two dimensions of professional planning work and AI type, this paper analyzes the technical uses and use modes of large models in urban planning research and practice, proposes a technical paradigm and model-construction method for embedding large models into professional urban planning work, and verifies their effectiveness through a professional large model for street walking safety. The conclusions are as follows.

First, the technical paradigm for embedding large models into professional urban planning work is to use professional large models with a knowledge structure of general knowledge plus domain knowledge to support the full diagnosis-inference-treatment working mode and the problem-oriented and law-oriented planning paradigms. Both paradigms follow the diagnosis-inference-treatment mode. Large models belong to cognitive intelligence and have the capacity to conduct diagnosis, inference and treatment through knowledge-based reasoning. Professional large models with planning domain knowledge can support professional urban planning work.

Second, the construction of professional planning large models should center on domain knowledge. This paper divides planning domain knowledge into diagnostic domain knowledge and treatment domain knowledge. Diagnostic domain knowledge supports the process from identifying spatial problems to inferring their causes, while treatment domain knowledge supports the process from inferring causes to proposing planning strategies.

Diagnostic training and treatment training enable the model to learn these two types of knowledge. Through this route, the limitations of general large models in domain knowledge can be addressed, and the diagnosis-inference-treatment workflow can be supported.

Third, the empirical case verifies that professional large models can be embedded into planning practice as professional assistants. In the case of street walking safety, the professional large model can diagnose spatial problems, infer the causes of poor walking safety and propose planning strategies. It can also conduct large-scale diagnosis and strategy generation across all street segments within Shanghai's Inner Ring. Evaluation results show that its cognitive reasoning ability approaches the average level of professionals and is much stronger than that of an untrained general large model.

**5.2 Discussion**

The above conclusions indicate that the key to applying large models to professional urban planning work is not merely to use a general model as a new interface or a public simulator, but to construct professional models with domain knowledge and to embed them into the actual workflow of planning. The diagnosis-inference-treatment mode provides a clear bridge between planning knowledge and model capability. It enables large models to move from perceiving spatial elements toward reasoning about spatial problems and generating strategies.

Professional large models should still be used with caution. Their outputs are references for planning decisions, not substitutes for professional judgment. Value judgments, public-interest balancing, local institutional constraints and implementation feasibility remain central to planning work. These elements cannot be fully reduced to domain-knowledge training data. Planners should therefore evaluate model outputs and retain final responsibility for decisions.

The case in this paper focuses on street walking safety. Future research can extend the framework to other professional planning tasks, such as land-use optimization, community renewal, transport demand management and ecological space protection. It is also necessary to develop richer diagnostic and treatment domain knowledge bases, improve the interpretability and reliability of professional large models, and establish evaluation systems that combine model performance, professional review and planning implementation effects.

**Notes**

① Street walking safety here refers to the safety level in the hierarchy of walking needs and focuses on the influence of natural surveillance and environmental disorder on pedestrian safety perception and walking willingness.

② The full-street diagnosis uses street-view imagery and related spatial data within Shanghai's Inner Ring as model inputs. The one-hour processing time refers to batch inference under the model configuration used in the empirical case.

③ Accuracy measures the overall proportion of correct judgments. F1-score considers both precision and recall and is therefore more indicative of sensitivity and reliability when evaluating the model's ability to identify problem streets in practice.

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