Urban Planning Agent: Concepts, System Architecture, and Reflections on Practice

Authors
WU Zhiqiang; WU Tao; ZHOU Mimi; ZHANG Jiaqi; JIANG Qingrui; YANG Shujie; CHEN Yijie; WU Xiaolong

Abstract
Artificial intelligence is reshaping the knowledge production, methodological organization, and governance mechanisms of urban planning. As urban systems become more complex, public-interest coordination more demanding, and planning implementation more uncertain, urban planning urgently needs a professional intelligent methodology that covers the whole planning process. This paper proposes the concept of the urban planning agent, defined as a professional intelligent system that uses multi-source urban data as its perceptual basis, draws on planning knowledge, regulations and standards, model-based methods, case experience, and implementation feedback, and makes judgments according to public value, spatial order, and governance objectives. The paper discusses the conceptual connotation, capability structure, system architecture, application map, and Chinese institutional context of urban planning agents. It proposes an eight-dimensional capability framework of perception, cognition, simulation, creation, decision-making, execution, coordination, and learning; constructs a four-layer operating architecture of data, computation, decision-making, and application; and identifies eight types of specialized agents: spatiotemporal sensing, regularity cognition, planning simulation, plan-making, action decision-making, organizational coordination, emergency response, and knowledge iteration. In China, urban planning agents should be embedded in the territorial spatial planning system and aligned with unified natural-resource management, urban assessment, urban regeneration, and digital government construction. Their operation should be supported by five databases covering natural resources, urban construction, socio-economic conditions, planning standards and regulations, and planning cases. Urban planning agents can help shift urban planning from stage-based plan preparation toward continuous spatial governance, offering theoretical and practical pathways for territorial spatial governance and human-AI collaborative planning.

Keywords
urban planning agent; intelligent planning; urban planning methods; spatial governance; human-agent collaboration

1 Traditional Urban Planning Calls for Intelligent Methodological Empowerment

In long-standing planning practice, conventional methods have often contained blind spots in survey analysis, plan preparation, technical review, and implementation management. These blind spots may appear as insufficient quantitative support or as imprecise diagnosis [1-4]. The overall ecological rationality of planning has also long been constrained by arbitrary authority, intuition-based decisions, neglect of residents' objective needs, and a preference for spatial formalism. It has not yet systematically mined the internal intelligence of urban life or the rules by which cities evolve and iterate, making it difficult to form a complete disciplinary methodology [5].

Profound changes in urban development now require planning to expand its capacity boundary. Non-systematic surveys cannot capture, in a timely manner, the deeper causes of change in urban operation and social demand. Plans led by a single authority cannot adequately balance multiple objectives, constraints, and scenarios. Implementation mechanisms divided among departments cannot easily coordinate across professions, actors, and administrative levels. Deviations, performance results, and newly emerging issues during implementation also cannot be fed back promptly into plan preparation, review, and dynamic maintenance [6-7]. The key challenge for urban planning is therefore no longer merely to improve efficiency in isolated links, but to give birth to new planning, innovate the planning paradigm, and systematically reshape capacities across the whole process.

Digital and intelligent technologies offer a historic opportunity to empower both the thinking methods and working methods of urban planning. The introduction of digital-intelligent planning systems, including city information modeling (CIM), urban operating centers, and cross-generational digital twins, has significantly improved data mining, spatial analysis, plan generation, operation monitoring, and governance coordination [8-10]. Yet these point-based improvements are still insufficient to produce an integrated leap from survey diagnosis to plan-making and implementation operation. Existing technical applications remain relatively fragmented: some systems emphasize data-platform construction but do not intervene in action commands or overall coordination, and they have not yet formed a continuous method system linking problem identification, scenario simulation, rule checking, implementation feedback, and actor coordination [11]. The deeper impact of intelligent technology on planning lies in quantification, ecosystem thinking, and the lifecycle integration of thought and action, which together enable a historic reorganization of planning knowledge, planning judgment, and planning action.

Recent developments in large models and agent technologies have gradually enabled intelligent systems to understand tasks, perceive environments, call tools, retain process memory, plan actions, and learn from feedback. This creates new methodological possibilities for urban planning. Current-condition identification, problem diagnosis, scenario simulation, plan generation, rule review, public communication, implementation monitoring, and interdepartmental coordination no longer need to be separated work segments; they can be organized into an intelligent process that runs continuously, feeds back dynamically, and evolves collaboratively [12-16]. Against this background, urban planning needs a concept with clear disciplinary attributes and professional orientation to explain and guide the methodological transformation brought by artificial intelligence.

On this basis, this paper proposes the concept of the urban planning agent. An urban planning agent is a professional intelligent system oriented toward the whole urban-planning process. It can assist or participate in perception, cognition, simulation, creation, decision-making, execution, and learning in planning. Its core purpose is not to replace planners in single tasks, but to organize scattered planning data, knowledge rules, models, methods, case experience, and implementation feedback into an operable, checkable, and iterable method system. In this way, it reconstructs the relations among urban-state perception, professional cognition, value judgment, spatial action, and implementation feedback [17-18].

This paper develops the concept of the urban planning agent in four respects. First, it defines the basic connotation of the urban planning agent and distinguishes it from planning support systems, smart-city platforms, urban brains, and general-purpose AI agents. Second, it proposes a capability structure composed of perception, cognition, simulation, creation, decision-making, execution, coordination, and learning, and explains how it serves the whole planning process. Third, it builds an application map for eight types of specialized planning agents: spatiotemporal sensing, regularity cognition, planning simulation, plan-making, action decision-making, organizational coordination, emergency response, and knowledge iteration. Fourth, drawing on the authors' nearly twenty years of exploration in digital-intelligent planning since 2006, especially five consecutive rounds of intelligent-planning research projects of the Chinese Academy of Engineering since 2016, it systematically summarizes experience gained through experimentation, trial and error, reflection, and iteration. The discussion draws on 96 projects and studies covering urban-regional strategy, territorial spatial master planning, urban design, urban regeneration, city image, urban color, and urban innovation vitality, and for the first time synthesizes two decades of digital-intelligent practice and ten years of theoretical thinking on AI-empowered planning.

2 Global Development of Urban Planning Agents

2.1 Five Historical Stages in the Development of Urban Planning Agents

The foundations of intelligent planning systems can be traced to nearly a century of related research, from the early twentieth-century urban morphology of the Conzenian school and the macro traffic models of the 1950s to the most recent frontier explorations that combine large models with planning tasks in 2025. In temporal terms, related research has grown explosively since 2023, the year when Park et al. proposed generative agents and the authors identify the first year of AIGP, or Artificial Intelligence Generated Planning. This marks the movement of AI from urban recognition, analysis, and prediction into the generation of planning schemes and design representation.

2.1.1 Stage 1: Emergence Based on Rules and Symbolic Logic, 1982-1996

This stage was based on complex adaptive systems (CAS), cellular automata (CA), and early multi-agent systems (MAS). Planning began to treat the city as a dynamic "living body" rather than a static blueprint [19]. Its core feature was bottom-up rule simulation: land, roads, vehicles, buildings, parcels, capital, and market demand were abstracted as urban micro-actors, while symbolic logic and transformation rules were used to simulate the evolution of urban spatial form. Drawing on 1,700 land-development cases in Shanghai, the authors' early research explored "soft information" and the simulation of urban spatial evolution [20-21]. From 1988 to 1992, related methods were further applied to spatial analysis in Hamburg, Frankfurt, and Berlin, with computer and digital-intelligent processing technologies gradually introduced [22]. This stage expressed the pursuit of "ecological rational planning" for cities and laid an epistemological foundation for large urban databases and computing platforms. The authors' team began building its first-generation urban big database in 1988.

2.1.2 Stage 2: Breakthroughs in Data Mining and Perceptual Computing, 1996-2006

This stage was grounded in urban informatics, spatial data science, conventional machine learning, and early neural networks. Intelligent planning research began to shift from rule-driven to data-driven methods. Its core feature was data reduction and feature extraction for planning and design projects. Through multi-source spatiotemporal data, scene images, microclimate simulation, hydrological environments, transport economics, and dynamic activity data, it produced a comprehensive perception of cities and sites. The planning simulation for Shanghai Expo was an important practice in this stage. For 70 million total visitors, daily flows of one million people, 256 pavilions, and a 6.28 km2 park, the team simulated million-person spatial distribution every day from 9:00 a.m. to midnight, compared multiple schemes, identified high-risk crowding sites, and promoted plan optimization. In particular, ten sites most likely to experience stampede risks were identified and repeatedly optimized until the risks were eliminated. The Expo simulation marked the entry of planning big-data methods from conceptual exploration into large-scale engineering practice. Its 22,525 spatial units represented a world-first scale in urban planning simulation, and the team also iterated the world's largest second-generation urban big database during this stage.

2.1.3 Stage 3: Formation of Urban Intelligence Theory and Generative Logic, 2006-2016

This stage was based on deep learning, reinforcement learning, multimodal regression, generative models, and explainable methods. Intelligent planning research began to form the meta-logic loop of "perception-judgment-action-learning" for planning agents. Around 2012, the authors' team systematically proposed the theory of City IQ, emphasizing that cities not only need to be perceived and diagnosed but also need capacities for judgment, action, and learning [23]. The core feature of this stage was the shift from diagnosis to generation: intelligent systems no longer only produced evaluation results, but also began to form plan-generation logics that could be understood, compared, and traced. AI entered planning scenarios such as functional integration, waterfront quality enhancement, science-and-innovation space organization, and conceptual design generation.

2.1.4 Stage 4: Systemic Breakthrough in AI-Empowered Planning, 2016-2023

After 2016, intelligent planning research became fully connected with global AI development and entered a stage of systemic breakthroughs in AI-empowered cities and planning. The authors participated in the Chinese Academy of Engineering's strategic AI 2.0 project, focusing on the empowerment of cities and planning by AI. Deep reinforcement learning (DRL), generative adversarial networks (GANs), multimodal learning, and explainable AI methods such as XAI and SHAP moved intelligent systems from analytical tools into design. This stage had three main features. First, planning moved from diagnosis to generation, enabling street-, community-, and district-scale layout simulation under complex spatial constraints. Second, it sought to break the "black box" by making the judgment path of the agent understandable and checkable by planners. Third, it realized multimodal integration, jointly processing spatial vectors, remote-sensing imagery, street-view images, and planning texts. During this stage, the authors' team promoted the practical application of AI-based urban planning and developed intelligent algorithmic frameworks to support plan generation and spatial-quality improvement.

2.1.5 Stage 5: Maturity Through Large-Model Drive and Full-Process Human-Agent Interaction, 2024-Present

Since 2024, urban planning agents have entered a stage driven by large models and full-process human-agent interaction (HAI). Multimodal large language models (MLLMs), LLM-agent architectures, and federated learning have moved agents from single tools toward platform-based, systematic, and collaborative systems. The core feature is a full-process HAI ecosystem. Agents can support platform construction, project design, academic validation, and engineering representation, forming end-to-end capacities from conceptual simulation to high-fidelity outputs. At the same time, in sensitive fields such as territorial spatial planning, intelligent platforms have begun to develop multilevel classification, security protection, and whole-process control. Agents trained on professional literature, planning drawings, policy standards, and engineering experience are becoming "expert systems 2.0" with sectoral common sense. The authors emphasize the deep integration of machine intelligence and human wisdom, so that planning agents become not merely drawing tools but digital collaborators for research innovation, technical-route design, and spatial-governance coordination.

2.2 Five Development Directions for Urban Planning Agents

2.2.1 Direction 1: Large Language Models and Multi-Agent Systems: Cognitive and Collaborative Brains

This direction concerns the underlying cognitive framework of agents, including cognitive architecture, long-term memory, task planning, tool calling, role division, and consensus formation. Its purpose is to enable agents to understand tasks, coordinate multiple parties, and form action judgments in complex urban contexts. It can also transform stakeholders such as governments, planners, developers, and residents into role agents with different objectives and constraints, thereby simulating the social games of real planning. Symbolic and rule-based systems from the 1970s to the 1990s, together with the work of Wooldridge et al. [24], laid a theoretical foundation for distributed agents. From the 2000s to the 2010s, distributed AI and multi-agent systems were widely used in land-use scenario simulation and residential location. In 2016, the authors' CityGo urban game model also demonstrated the importance of collaborative decision-making through multi-actor game simulation. Since 2023, LLM-driven generative agents, represented by Park et al.'s Generative Agents [25], have enabled memory, reflection, and personified behavior, while Hong et al.'s MetaGPT [26] further demonstrates the possibility of role division and workflow organization. The main bottlenecks are memory drift in long-cycle simulations, deadlock and group polarization in social games, and insufficient role authenticity.

2.2.2 Direction 2: Generative Urban Design and Spatial-Geometric Generation: Embodied Entities and Hands

This direction determines whether planning agents can translate textual goals, planning standards, and spatial constraints into visible and assessable spatial schemes. From the 1980s to the 2000s, CAD and parametric modeling allowed designers to control geometry through rules and parameters. From 2016 to 2023, deep-learning spatial generation, including conditional generative models such as Pix2Pix [27], provided a foundation for spatial-image generation; reinforcement learning and graph neural networks were also used in urban land-use optimization. Since 2024, multimodal AI-agent approaches have begun to integrate diffusion models, ControlNet, large models, and GIS engines, moving planning tasks from semantic input toward spatial generation. The bottlenecks include semantic discontinuity in high-dimensional topology, distortion in cross-scale spatial generation, and instability in converting textual semantics into planning parameters.

2.2.3 Direction 3: Urban Morphology and Space Syntax: Professional Common Sense and Scientific Rigidity

Generative AI can produce schemes that appear plausible but lack professional grounding. Urban morphology and space syntax provide scientific constraints and an anti-hallucination baseline so that schemes are not only visually attractive but also consistent with the laws of spatial evolution. The classic qualitative morphology of the 1970s, including the Conzenian school and the Italian morphological tradition, analyzed urban fabric through historical maps. From the 1980s to the 2010s, space syntax and computational morphology matured, with Hillier et al. [28] establishing the theoretical foundation of space syntax and Batty [29] explaining urban spatial evolution from the perspective of complex systems. Since 2023, in a data-theory dual-driven stage, morphological knowledge has begun to be translated into knowledge graphs, evaluation functions, and generative constraints. The authors' team constructed "urban trees" at 30 m grid resolution over a forty-year period and classified 13,861 urban built-up areas into seven development types, showing that urban form has recognizable, generalizable, and learnable regularities. The difficulty lies in the limited ability of space syntax to fully express historical context and lived experience, and in the remaining gap between generative models and morphological theory.

2.2.4 Direction 4: Agent-Based Urban Population and Transport Simulation: Behavioral Sandboxes and Stress Testing

This direction is used to test the behavioral consequences and system performance of planning schemes in real operation. It extends from transport-demand prediction and road-network loading in the 1950s-1980s, through conventional agent-based models and microscopic transport simulation from the 1990s to the 2020s [30-31], to LLM-enabled social-behavior simulation since 2023. Further breakthroughs are needed in reconciling computing resources with real-time feedback, verifying emergent behavior, and closing the loop between simulation results and plan generation.

2.2.5 Direction 5: Multi-Objective Optimization and Planning Evaluation: Evolution and Steering

This direction supports planning agents in identifying conflicts, comparing scheme performance, and making iterative corrections. Single-objective numerical optimization from the 1960s to the 1990s used linear programming for problems such as facility location. Heuristic algorithms and multi-objective optimization from the 2000s to the 2020s, including methods such as NSGA-II, brought Pareto optimization into complex planning problems, while models such as ENVI-met provided tools for microclimate and environmental-performance assessment [32]. Since 2023, human-in-the-loop and reinforcement-learning approaches have incorporated planner experience and public feedback into scheme revision, forming collaborative optimization mechanisms. The key problems are that multi-objective weights depend heavily on expert experience, the value logics of different goals are difficult to unify into stable optimization functions, and master planners' intuition and aesthetic judgment are difficult to convert into executable parameters.

Table 1. Overview of the five major research directions related to urban planning agents

Technical direction	Corresponding capability	Support for urban planning agents	Main problems to be solved
Large language models and multi-agent systems	Cognition and coordination	Support task understanding, role division, tool calling, process memory, and multi-actor negotiation	Long-cycle memory drift, group polarization, and insufficient role authenticity
Generative urban design and spatial-geometric generation	Spatial production	Support land-use layout, road organization, building form, and spatial scheme generation	Unstable topological relations, insufficient cross-scale consistency, and difficulty embedding standards
Urban morphology and space syntax	Professional constraints	Support spatial-structure understanding, morphological-	Difficulty parameterizing morphological concepts and computationally

		regularity identification, and professional plan checking	expressing historical context and local experience
Urban population and transport simulation	Behavioral simulation	Support activity-chain simulation, transport-operation testing, and stress assessment of planning schemes	High computing cost, difficulty validating behavioral parameters, and insufficient closed-loop linkage with generation
Multi-objective optimization and planning evaluation	Feedback evolution	Support scheme comparison, conflict identification, performance assessment, and iterative optimization	Weights depend on negotiation, and value judgments are difficult to fully convert into optimization functions

Overall, the global development of urban planning agents is an intersection of urban-form cognition, behavioral simulation, spatial generation, planning evaluation, and human-agent collaboration. The five historical stages reveal an evolution from rule simulation and data perception to urban intelligence theory, AI empowerment, and large-model drive. The five research directions show how this evolution is translated into concrete capabilities: LLMs and multi-agent systems provide cognition and coordination, generative urban design provides spatial-production capacity, urban morphology and space syntax provide professional constraints, population and transport simulation provide behavioral testing, and multi-objective optimization and planning evaluation provide feedback correction. Urban planning agents should therefore be understood as composite systems formed by planning thought and method, urban-science models, and AI technologies. Their core value is to transform a planning practice long dependent on experience, drawings, and stage-based outputs into an intelligent methodology that can continuously perceive cities, explain regularities, generate schemes, check rules, feed back implementation, and coordinate governance.

3 Technical Architecture: Capability Composition of the Urban Planning Agent

The urban planning agent (UPA) is not a single AI model. It is a composite intelligent system that integrates multi-source spatiotemporal perception, professional knowledge reasoning, complex scenario simulation, and autonomous task execution. Its core logic is to use a large language model (LLM) as the cognitive "hub." Compared with traditional planning support systems (PSS), the urban planning agent places greater emphasis on goal decomposition, tool calling, process memory, feedback learning, and action coordination.

3.1 Conceptual Definition of the Urban Planning Agent

An urban planning agent is a professional intelligent system oriented toward the whole urban-planning process. It uses multi-source urban data as its perceptual basis, planning knowledge, regulations and standards, model methods, case experience, and implementation feedback as its cognitive support, and public value, spatial order, and governance objectives as the basis for judgment. It can assist or participate in perception, cognition, simulation, decision-making, execution, coordination, and learning, and can serve plan preparation, plan review, implementation monitoring, evaluation feedback, and governance coordination.

This definition involves three boundaries. First, the urban planning agent differs from ordinary efficiency tools. Tools mainly execute single commands, whereas agents can decompose tasks around goals, call tools, record processes, and revise actions in response to feedback. Second, it differs from general-purpose AI agents. Planning is not simply spatial generation in a general sense; it is a public decision-making process involving land resources, public services, ecological security, historical culture, social equity, and intergenerational responsibility [33-34]. Urban planning agents must therefore be embedded in planning objectives, regulatory constraints, local experience, and institutional procedures. Third, it differs from a single model. It is not the application of one algorithm to one task, but an operable planning-method system that organizes data, models, knowledge, rules, values, and feedback.

Methodologically, the urban planning agent reconstructs three sets of relations in planning. The first is the relation between facts and problems: urban-state data are transformed into spatial problems and governance issues. The second is the relation between knowledge and judgment: regulatory texts, expert experience, and case materials are organized into knowledge structures that can be reasoned with, explained, and checked. The third is the relation between schemes and actions: planning schemes are connected with review, implementation, monitoring, feedback, and coordination, so that they can be converted into real spatial-governance effects.

3.2 Capability Cultivation: Eight Specialized Planning Capabilities

The capability structure of the urban planning agent should be derived from the planning process itself. Urban planning is not a one-off information-processing activity, but a continuous process organized around urban states, spatial problems, future scenarios, value judgments, implementation actions, and feedback correction. Correspondingly, the urban planning agent needs eight capabilities: perception, cognition, simulation, creation, decision-making, execution, coordination, and learning. These are not a simple list of functions, but the capability-based expression of the planning process within an intelligent system.

Spatiotemporal perception corresponds to continuous understanding of actual urban conditions. Through data on natural resources, the built environment, population activity, industrial economy, transport travel, ecological environment, public services, public opinion, and implementation monitoring, the agent identifies changes in urban conditions and moves planning cognition from episodic surveys to continuous observation.

Regularity cognition corresponds to professional explanation of urban problems. The key is to transform data facts into explanations of spatial mechanisms, local phenomena into planning issues, and experiential judgments into reusable knowledge structures.

Future simulation corresponds to the organization of future possibilities. Through scenario setting, model simulation, scheme generation, and impact assessment, the agent converts future uncertainty into a comparable set of scenarios [35].

Plan creation corresponds to the substantive preparation of planning schemes and statutory outputs. Based on scenarios formed through simulation, the agent translates planning intentions into operable spatial blueprints and control rules through spatial-design generation, precise allocation of elements, drafting of planning texts, and automatic production of drawings.

Action decision-making corresponds to the handling of public value and multi-objective conflicts. It must organize objective systems, regulations and standards, evaluation models, expert experience, and public feedback into explainable grounds for judgment [36].

Top-down and bottom-up execution corresponds to the transformation of planning judgments into business processes, including rule checking, output generation, indicator calculation, spatial-conflict detection, task decomposition, project matching, and implementation sequencing [37].

Multi-party coordination corresponds to the organizational needs of planning as a public-governance process. Through goal decomposition, task tracking, information sharing, opinion aggregation, and scheme negotiation, the agent can promote more effective collaboration among departments, levels, regions, and social actors.

Machine learning corresponds to the dynamic updating of the planning system. Through case accumulation, implementation monitoring, public feedback, expert correction, and rule revision, it continuously optimizes knowledge structures, judgment rules, and action strategies. Together, these eight capabilities form a process-capability chain that enables the urban planning agent to grow from an information-processing tool into a whole-process planning-method system.

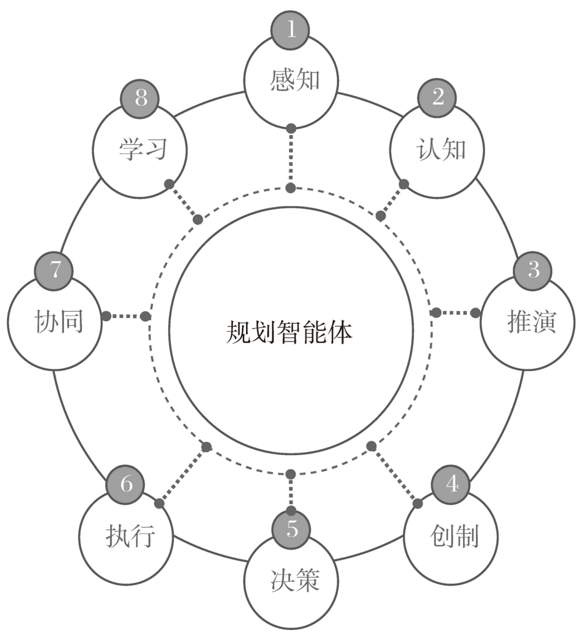


Figure 1. Capability structure of the urban planning agent.

3.3 Basic Architecture: Data Layer, Computation Layer, Decision-Making Layer, and Application Layer

The operation of planning-agent capabilities requires a clear system architecture. Combining the workflow of urban planning with the operating logic of intelligent systems, the urban planning agent can be composed of four layers: data, computation, decision-making, and application. The data layer provides urban-state and planning information, the computation layer conducts problem identification and scenario simulation, the decision-making layer forms value trade-offs and rule judgments, and the application layer promotes task execution and governance coordination. The theoretical significance of the four-layer architecture is that it organizes urban data, planning knowledge, model methods, public value, and governance action into an operable, checkable, and iterable method system.

The data layer is the factual foundation. Its focus is the spatialized, temporalized, object-oriented, and semantic organization of model data. Data on natural resources, urban construction, socio-economic conditions, public opinion, and implementation monitoring respectively support baseline identification, current-condition judgment, demand analysis, understanding of claims, and feedback adjustment.

The computation layer is the stage of cognitive generation. It converts data into problem identification, spatial analysis, scenario simulation, scheme generation, impact assessment, and rule-checking results. It can call methods such as geospatial analysis, urban simulation, knowledge graphs, machine learning, generative models, and multi-objective optimization, but its core task is to transform complex urban phenomena into explainable planning problems.

The decision-making layer is the stage of value organization. It places computational results within public value, planning objectives, regulatory standards, expert experience, and implementation constraints to form comprehensive judgments. Urban planning is a public choice that must be explainable, reviewable, and accountable in specific contexts.

The application layer is the stage of action transformation. It introduces data, computation, and decision results into plan preparation, plan review, implementation monitoring, public communication, emergency response, and interdepartmental coordination. New data, new problems, and new feedback generated during application return to the data layer, driving continuous updating of models, rules, and application methods. The four-layer architecture thereby forms a closed-loop mechanism connecting urban state, planning cognition, public value, and governance action, supporting the urban planning agent throughout the whole planning process.

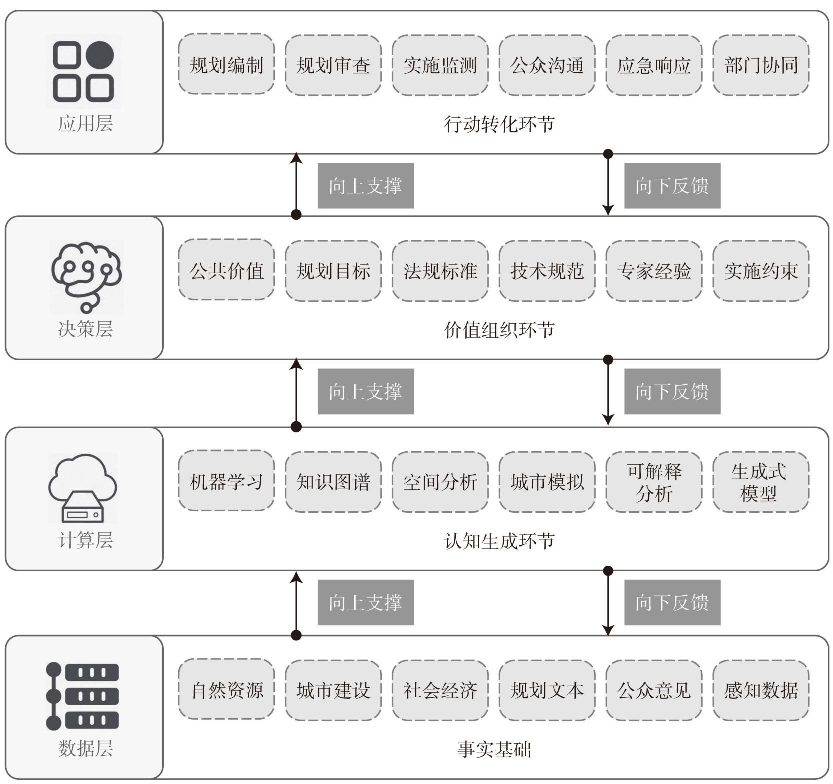


Figure 2. Basic architecture of the urban planning agent.

4 Application Map: Eight Types of Specialized Agents for the Whole Planning Process

When urban planning agents enter the planning field, their value lies in the systematic organization of the whole planning process. Urban planning must absorb public demands, identify urban problems, form spatial schemes, maintain institutional rules, evaluate implementation effects, respond to abnormal risks, and coordinate multi-actor action. For ease of discussion, this paper refers to professional agents oriented toward specific planning tasks as specialized agents. Across the whole planning process, the urban planning agent can be summarized into eight types: spatiotemporal sensing, regularity cognition, planning simulation, plan-making, action decision-making, organizational coordination, emergency response, and knowledge iteration. They correspond respectively to the core links of urban-state diagnosis, spatial-regularity identification, scheme formation, rule review, implementation evaluation, action coordination, resilience governance, and planning-knowledge updating.

4.1 Spatiotemporal Sensing Agent: Continuous Identification of Urban Conditions

The spatiotemporal sensing agent addresses multi-source information on natural resources, the built environment, population activity, industrial economy, transport travel, ecological environment, public services, public opinion, and implementation monitoring [38-39]. It continuously identifies urban operating conditions and spatial change. Through spatialized, temporalized, and object-oriented processing, it converts scattered spatial data, social claims, and operational information into planning-perception results with location, type, intensity, and evolutionary trend. It shifts urban cognition from episodic surveys to continuous observation and provides a reliable base map for subsequent regularity cognition and scenario simulation.

4.2 Regularity Cognition Agent: Diagnostic Explanation of Spatial Mechanisms

The regularity cognition agent addresses compound issues such as population structure, spatial functions, transport operation, public services, ecological environment, housing supply, and governance capacity [40]. It reveals the spatial structure, operating mechanisms, and implementation deviations behind observed phenomena. By transforming data facts into spatial-mechanism explanations, local phenomena into planning issues, and experiential judgments into reusable knowledge structures, it supports urban-problem diagnosis, governance-priority judgment, and the selection of planning intervention directions.

4.3 Planning Simulation Agent: Organization and Comparison of Future Scenarios

The planning simulation agent addresses the uncertainty of urban development. Through scenario setting, model simulation, impact assessment, and multi-scheme comparison, it converts factors such as demographic change, industrial evolution, transport organization, ecological constraints, and renewal rhythm into comparable future scenarios. Its core function is to help planners see the spatial consequences of different choices and turn difficult future problems into scenario sets that can be calculated, compared, and discussed.

4.4 Plan-Making Agent: Creation of Spatial Schemes and Statutory Outputs

The plan-making agent supports the generation of spatial schemes and statutory outputs. Under clearly defined planning objectives, baseline constraints, implementation conditions, and human supervision, it assists in organizing spatial structures, optimizing land-use layouts, accurately allocating elements, drafting texts, and expressing drawings [41]. It can expand the breadth of scheme exploration and improve the efficiency of output representation, but problem definition, goal setting, rule configuration, and value judgment remain the planner's key responsibilities.

4.5 Action Decision-Making Agent: Multi-Objective Trade-Offs and Scheme Selection

The action decision-making agent addresses conflicts among ecological security, development efficiency, spatial equity, historical culture, public services, resilience and safety, and implementation cost. It organizes objective systems, regulatory standards, evaluation models, expert experience, and public feedback into explainable grounds for judgment. It supports scheme comparison, risk identification, and action selection, moving planning decisions from single technical optimums toward comprehensive trade-offs oriented to public value and ensuring that machine computation is subordinate to planning rationality and governance responsibility.

4.6 Organizational Coordination Agent: Governance Coordination of Multi-Actor Action

The organizational coordination agent addresses cross-departmental tasks such as urban regeneration, transport improvement, ecological restoration, public-service upgrading, industrial-space adjustment, and regional cooperation. It structurally organizes planning objectives, spatial tasks, policy instruments, and implementation actors. It supports goal decomposition, responsibility linkage, progress tracking, and feedback warnings, thereby forming clearer collaborative action relations among departments, levels, regions, and social actors.

4.7 Emergency Response Agent: Spatial Response to Abnormal Risks

The emergency response agent addresses extreme weather, flood disasters, public-health events, infrastructure failures, and major public-safety incidents, supporting risk identification, resource dispatch, and rapid response [42]. It connects prevention before events, handling during events, and feedback after events, feeding problems exposed by abnormal incidents, such as weak infrastructure, insufficient public space, poor passage organization, and inadequate community resilience, back into territorial spatial planning, detailed planning, and infrastructure construction.

4.8 Knowledge Iteration Agent: Continuous Updating of Planning Experience

The knowledge iteration agent addresses practice materials such as planning cases, review comments, implementation performance, public feedback, expert correction, and rule revision. It continuously accumulates reusable planning knowledge resources. It converts experience, deviations, and lessons from planning processes into bases for knowledge updating, rule optimization, and model correction, enabling the planning agent to develop capacities for relearning, recalibration, and dynamic evolution through continuing practice.

4.9 Collaborative Operation Mechanism of the Eight Specialized Agents

The eight specialized agents jointly form the group structure of the urban planning agent. The spatiotemporal sensing agent provides the base of urban conditions; the regularity cognition agent explains spatial mechanisms; the planning simulation agent organizes future scenarios; the plan-making agent generates spatial schemes and statutory outputs; the action decision-making agent supports multi-objective trade-offs; the organizational coordination agent safeguards multi-actor action; the emergency response agent addresses abnormal risks; and the knowledge iteration agent accumulates feedback experience and updates knowledge rules.

The key to collaboration among the eight agents is the continuous relation of "state-regularity-scenario-scheme-decision-coordination-response-iteration": urban conditions are continuously perceived, spatial regularities are identified and explained, future scenarios are organized and compared, planning schemes are generated and represented, action choices are comprehensively assessed, multi-actor tasks are jointly advanced, risk events are quickly handled, and implementation feedback and practical experience are continuously accumulated. In this way, the urban planning agent develops from an auxiliary tool attached to existing procedures into an intelligent organizational mechanism that supports the whole process of urban planning.

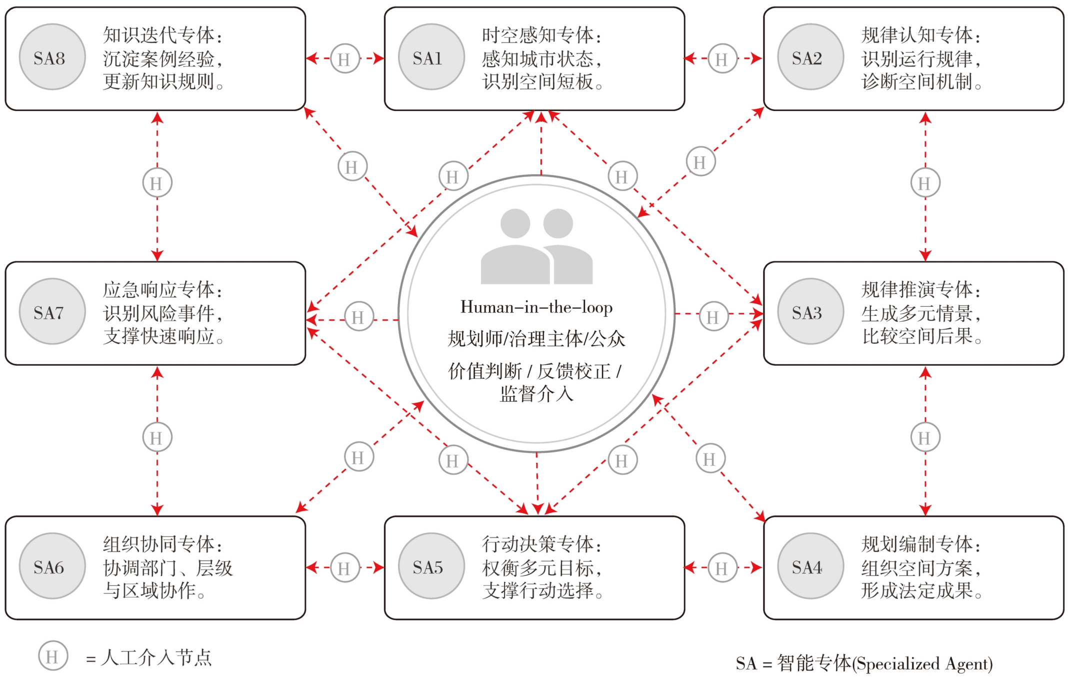
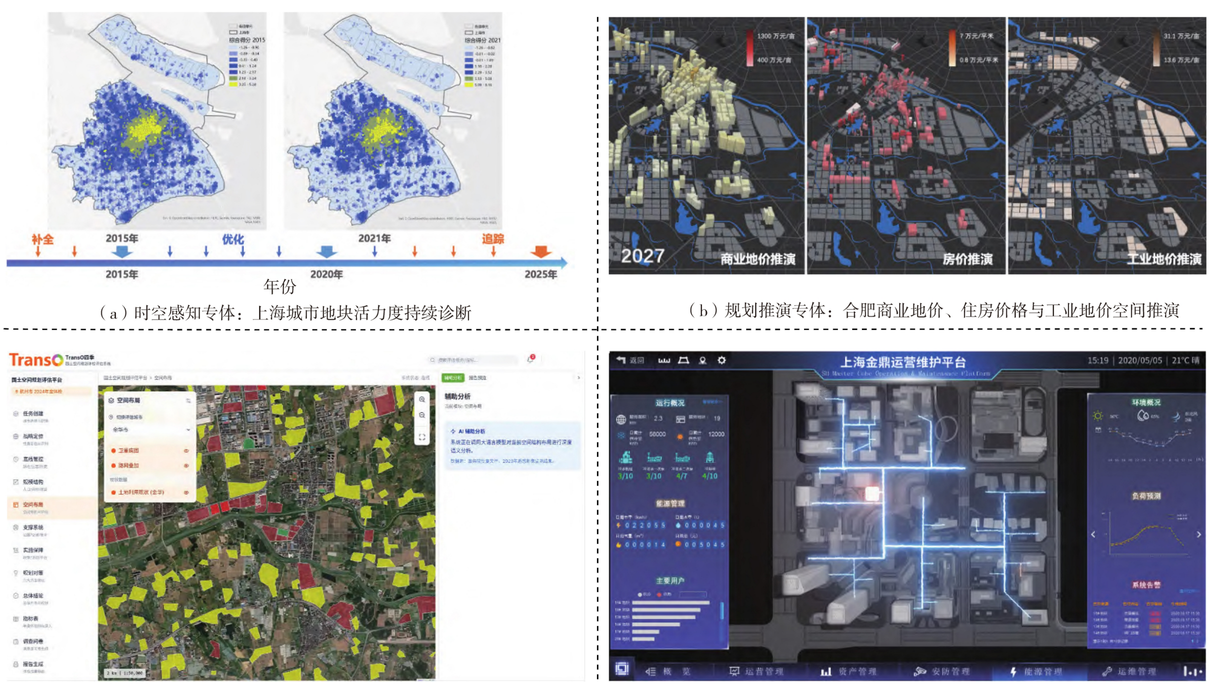


Figure 3. Ecological rationality framework of interrelations among eight specialized urban planning agents.



（a）时空感知专体：上海城市地块活力度持续诊断

（b）规划推演专体：合肥商业地价、住房价格与工业地价空间推演

（c）行动决策专体：兰溪国土空间开发保护评估与研判

（d）知识迭代专体：上海金鼎聪明城区能源运行监测、反馈与知识更新

Figure 4. Applications of selected specialized urban planning agents: (a) spatiotemporal sensing agent, continuous diagnosis of parcel vitality in Shanghai; (b) planning simulation agent, spatial simulation of commercial land price, housing price, and industrial land price in Hefei; (c) action decision-making agent, assessment and judgment of territorial spatial development and protection in Lanxi; (d) knowledge iteration agent, energy-operation monitoring, feedback, and knowledge updating in Shanghai Jinding Smart District.

5 Conclusion: Urban Planning Agents in the Chinese Context: Institutional Foundations and Knowledge Support

5.1 Knowledge Support for Urban Planning Agents in China: A Five-Database System

The operation of urban planning agents depends on a stable, systematic, and updatable knowledge foundation. Chinese urban planning has rich data sources, institutional rules, and practical experience, yet these resources have long been scattered across departments, platforms, planning outputs, and project processes [43]. For planning agents to form professional judgments, these dispersed resources need to be organized into a knowledge system with planning meaning.

Around the main tasks of Chinese planning practice, this knowledge support can be summarized as five databases: natural resources, urban construction, socio-economic conditions, standards and regulations, and planning cases. The key to the five databases is not the accumulation of materials, but the organization of planning knowledge. Only by organizing data, rules, models, cases, and feedback into a callable, explainable, and updatable knowledge system can planning agents form genuinely professional planning-judgment capacity.

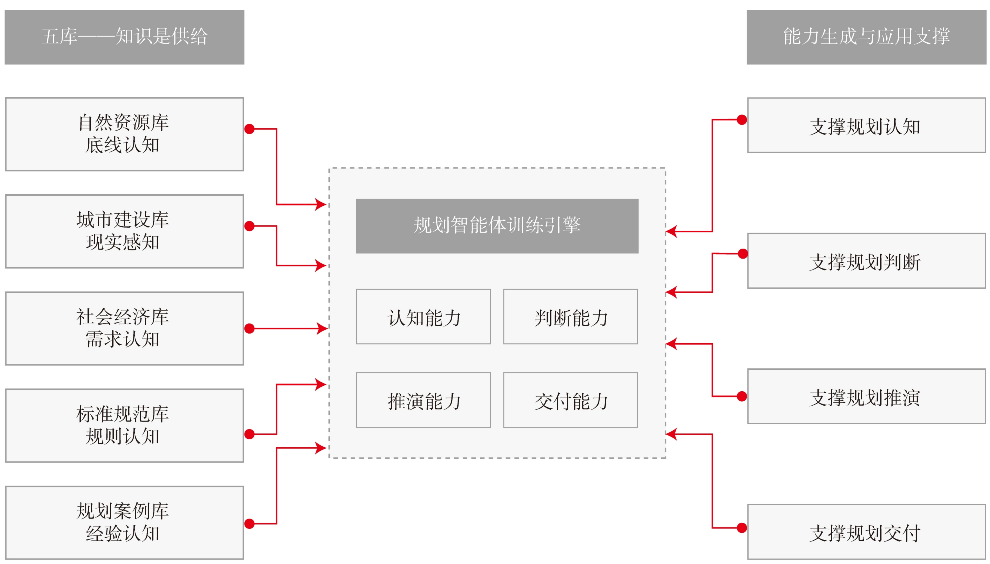


Figure 5. Five-database support system for the urban planning agent.

5.2 Promoting a Methodological Leap in Planning for the Intelligent Age

The proposal of the urban planning agent marks a new stage in the relationship between urban planning and artificial intelligence. From the perspective of disciplinary development, it raises core questions that urban planning must answer in the intelligent age: How can cities be continuously understood? How can problems be accurately judged? How can schemes be rationally simulated? How can rules be transmitted steadily? How can value be embedded in intelligent processes? How can implementation feed back into the planning system? These questions have gone beyond ordinary technical application and point to theoretical renewal within the discipline of urban planning. Planning should not treat AI merely as an external tool, nor should it remain at the level of technology transplantation. It should actively construct an intelligent-planning theory grounded in the discipline, placing complex urban systems, planning knowledge engineering, human-agent collaborative decision-making, public-value constraints, and spatial-governance mechanisms within a unified framework to form a future-oriented planning methodology.

From the perspective of professional practice, planning agents will change the capability structure of planning work. The core capacities of future planners will focus more on problem definition, goal setting, value judgment, rule organization, scenario interpretation, collaborative governance, and responsibility control. Agents can expand planners' perceptual range, simulation capacity, comparative ability, and feedback capacity, but planning direction, public value, and ultimate responsibility must still be jointly held by the professional community and public-governance institutions. The more planning enters the intelligent age, the more the profession needs to strengthen professional rationality and safeguard the bottom lines of public interest, spatial equity, ecological security, cultural continuity, and long-term responsibility. The development of urban planning agents should not weaken human professional judgment; rather, it should enhance planners' ability to handle complex urban problems [44].

The key to building urban planning agents is to transform the planning profession's long-accumulated data, rules, cases, experience, and value judgments into knowledge systems that can be organized, explained, reviewed, and updated. Agents without planning knowledge can only remain general intelligent tools. Agents without public-value constraints easily fall into efficiency-first and local-optimum logics. Agents without implementation feedback cannot genuinely serve urban governance. Looking ahead, urban planning agents should take the five databases of natural resources, urban construction, socio-economic conditions, standards and regulations, and planning cases as their foundation; continuously accumulate knowledge, methods, and experience from planning practice; and form professional capacities that support plan preparation, review, implementation, evaluation, and collaborative governance. In doing so, they can contribute Chinese wisdom and Chinese experience to the global development of urban planning theory and professional practice in the intelligent age.

References

[1] GALLOTTI R, SACCO P, DE DOMENICO M. Complex urban systems: challenges and integrated solutions for the sustainability and resilience of cities[J]. Complexity, 2021(1): 1782354.

[2] Zhou Changlin, Bai Yu, Xie Shuimu. Urban spatial performance oriented toward high-quality development: multi-objective paradoxes and an evaluation model[J]. Urban Planning Forum, 2022(4): 58-63.

[3] Yang Xuanmei. Territorial spatial resilience: conceptual framework and implementation pathways[J]. Urban Planning Forum, 2021(3): 112-118.

[4] Wu Zhiqiang, Liu Xiaochang, Zhao Gang, et al. Replacing simple expansion with spatial-benefit orientation: key evaluation indicators for urban governance[J]. Urban Planning Forum, 2021(5): 15-22.

[5] ZHOU X, LIN Y, MONSTADT J, et al. Examining collaborative planning processes and outcomes in urban regeneration: a deliberative turn in China?[J]. Urban Studies, 2024, 62(4): 682-699.

[6] Cao Chunhua, Lu Tao, Li Peng, et al. Monitoring, evaluation, and early warning in territorial spatial planning: connotation, tasks, and technical framework[J]. Urban Planning Forum, 2022(6): 88-94.
[7] Sun Shiwen. Basic research on the implementation-supervision system for territorial spatial planning[J]. Urban Planning Forum, 2024(2): 12-17.
[8] PAN H, GEERTMAN S, DEAL B, et al. Planning support for smart cities in the post-COVID era[J]. Journal of Urban Technology, 2022, 29(2): 1-5.
[9] Wu Zhiqiang, Gan Wei, Zang Wei, et al. The concept and development of city information modeling (CIM)[J]. City Planning Review, 2021, 45(4): 106-113.
[10] BATTY M. Digital twins in city planning[J]. Nature Computational Science, 2024, 4(3): 192-199.
[11] RITTENBRUCH M, FOTH M, MITCHELL P, et al. Co-designing planning support systems in urban science: the questions they answer and the questions they raise[J]. Journal of Urban Technology, 2021, 29(2): 7-32.
[12] SON T H, WEEDON Z, YIGITCANLAR T, et al. Algorithmic urban planning for smart and sustainable development: systematic review of the literature[J]. Sustainable Cities and Society, 2023, 94: 104562.
[13] PENG Z R, LU K F, LIU Y, et al. The pathway of urban planning AI: from planning support to plan-making[J]. Journal of Planning Education and Research, 2023, 44(4): 2263-2279.
[14] Wu Zhiqiang, Gan Wei, Liu Chaohui, et al. AI city: theory and model architecture[J]. Urban Planning Forum, 2022(5): 17-23.
[15] Gan Wei, Wu Zhiqiang, Wang Yuankai, et al. Construction of a theoretical model for AIGC-assisted urban design[J]. Urban Planning Forum, 2023(2): 12-18.
[16] ZHENG H, YUAN P F. A generative architectural and urban design method through artificial neural networks[J]. Building and Environment, 2021, 205: 108242.
[17] Wu Zhiqiang, Zhou Mimi, Liu Qi, et al. "Cross-generational twin": mapping the life characteristics of cities[J]. Urban Planning Forum, 2024(1): 9-17.
[18] Wu Zhiqiang, Gan Wei, Li Shuran, et al. "Urban collective brain": theoretical model and key issues[J]. Urban Planning Forum, 2023(6): 20-26.
[19] Wu Zhiqiang. Changes in the thinking methods of urban planning[J]. Urban Planning Forum, 1986(5): 1-7.
[20] Wu Zhiqiang. How to handle soft information: multi-criteria analysis methods in urban land-use planning[J]. Urban Planning Forum, 1985(3): 41-49.
[21] Wu Zhiqiang. Basic research on urban land development in Shanghai: distribution of development volume, value measurement, and development mechanism[D]. Shanghai: Tongji University, 1984.
[22] WU Z Q. Globalisierung der grossstadte um die jahrtausendwende: forschung[D]. Berlin: Technische Universitat Berlin, 1994.
[23] WU Z Q, PAN Y, YE Q, et al. The city intelligence quotient (City IQ) evaluation system: conception and evaluation[J]. Engineering, 2016, 2(2): 196-211.
[24] WOOLDRIDGE M, JENNINGS N R. Intelligent agents: theory and practice[J]. The Knowledge Engineering Review, 1995, 10(2): 115-152.
[25] PARK J S, O'BRIEN J, CAI C J, et al. Generative agents: interactive simulacra of human behavior[C]//Proceedings of the 36th Annual ACM Symposium on User Interface Software and Technology (UIST '23). San Francisco, CA, USA: Association for Computing Machinery, 2023: 1-22.

[26] HONG S, ZHUGE M, CHEN J, et al. MetaGPT: meta programming for a multi-agent collaborative framework[C]//The Twelfth International Conference on Learning Representations (ICLR 2024). Vienna, Austria: OpenReview.net, 2024.

[27] ZHENG Y, LIN Y, ZHAO L, et al. Spatial planning of urban communities via deep reinforcement learning[J]. Nature Computational Science, 2023(9): 748-762.

[28] HILLIER B, HANSON J. The social logic of space[M]. Cambridge: Cambridge University Press, 1989.

[29] BATTY M. Cities and complexity: understanding cities with cellular automata, agent-based models, and fractals[M]. Cambridge, MA: The MIT Press, 2007.

[30] HEPPENSTALL A, MALLESON N, CROOKS A. "Space, the final frontier": how good are agent-based models at simulating individuals and space in cities?[J]. Systems, 2016, 4(1): 9.

[31] AXHAUSEN K W, HORNI A, NAGEL K, et al. The multi-agent transport simulation MATSim[M]. London: Ubiquity Press, 2016.

[32] BRUSE M, FLEER H. Simulating surface-plant-air interactions inside urban environments with a three-dimensional numerical model[J]. Environmental Modelling & Software, 1998, 13(3-4): 373-384.

[33] Tian Li, Xia Jing. Land development rights and territorial spatial planning: governance logic, policy instruments, and practical applications[J]. Urban Planning Forum, 2021(6): 12-19.

[34] HERZOG R H, GONCALVES J E, SLINGERLAND G, et al. Cities for citizens! Public value spheres for understanding conflicts in urban planning[J]. Urban Studies, 2023, 61(7): 1327-1344.

[35] YAP J R, ROMAN O, ADEY B T, et al. Trends and opportunities in adaptive planning for the built environment: a literature review[J]. City and Environment Interactions, 2025, 26: 100196.

[36] SHEYDAYI A, DADASHPOOR H. The public interest: schools of thought in planning[J]. Progress in Planning, 2022, 165: 100647.

[37] NOARDO F, GULER D, FAUTH J, et al. Unveiling the actual progress of digital building permit: getting awareness through a critical state of the art review[J]. Building and Environment, 2022, 213: 108854.

[38] Bakowska-Waldmann E, Kaczmarek T. The use of PPGIS: towards reaching meaningful public participation in spatial planning[J]. ISPRS International Journal of Geo-Information, 2021, 10(9): 581.

[39] MARSHALL S, FARNDON D, HUDSON-SMITH A, et al. Urban design and planning participation in the digital age: lessons from an experimental online platform[J]. Smart Cities, 2024, 7(1): 615-632.

[40] Wu Jiang, Wang Xin, Chen Ye, et al. Challenges of urban health examination in megacities and Shanghai's practice[J]. Urban Planning Forum, 2022(4): 28-34.

[41] HONG Q, XIA J, LONG Y. Generative artificial intelligence in urban design: a review of recent applications[J]. Landscape Architecture, 2026, 32(12): 24-34.

[42] SAENZ DE TEJADA C, DAHER C, HIDALGO L, et al. Urban planning, design and management approaches to building urban resilience: a rapid review of the evidence[J]. Cities & Health, 2024, 8(5): 932-955.

[43] Niu Xinyi, Lin Shijia, Sang Tian, et al. Digital planning technology: data and knowledge[J]. Urban Planning Forum, 2024(2): 18-24.

[44] FU J, HAN H, SU X, et al. Towards human-AI collaborative urban science research enabled by pre-trained large language models[J]. Urban Informatics, 2024, 3(1): 8.

AI-assisted translation