Exploring Innovation in Urban-Rural Planning and Design Education through the Dual Drivers of Professional Knowledge and Artificial Intelligence: A Case Study of Residential Area Planning

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Abstract. Rapid advances in artificial intelligence, together with changes in the urban-rural planning profession and the restructuring of its knowledge system, have created new demands for educational reform. Traditional planning and design education - dominated by physical-space design, expert experience, and apprenticeship-style instruction - is increasingly unable to respond to the diversification of stakeholder interests in the era of urban regeneration or to accelerating technological change. Taking the reform of residential area planning and design education as an example, this paper explores a dual-driven model of urban-rural planning and design education based on 'professional knowledge + artificial intelligence'. It develops intelligent tools, including a large-language-model-based multi-agent interaction system and a low-code automatic scheme generator, to support a complete three-stage teaching process: preliminary planning, scheme generation, and post-evaluation. The proposed approach updates teaching content and methods while strengthening students' interdisciplinary learning, scientific reasoning, and design innovation.

Keywords: artificial intelligence; urban-rural planning education; residential area planning and design; large language model.

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1 Transformation of the Urban-Rural Planning Profession Calls for Educational Reform

In recent years, profound changes have taken place in both the domestic and international socioeconomic environment. With the downturn in the real-estate sector, the previous urban development model driven by land-based urbanization faces major challenges. Although urban regeneration courses have been added to urban-rural planning curricula, the traditional education model, which emphasizes the physical environment, has lagged behind the rapid transformation of urbanization. Apprenticeship-style studio teaching remains common, with students relying heavily on the professional experience of instructors.

Artificial intelligence is triggering a new wave of global technological change. Since OpenAI released the GPT series in 2022, generative foundation models have spread rapidly across a wide range of industries. In planning education, courses in urban big data and urban informatics have provided a foundation for applying AI to urban-rural planning. These courses, however, tend to focus on data processing and analytical methods and emphasize data-driven research on urban issues. In response to AI, planning methods should gradually move from empirical reasoning, classical theory, and regulatory compliance toward big-data analysis and AI-assisted decision-making. Planners and students need to address urban problems through scientific logic and process-oriented thinking, while greater attention should be paid to technological innovation, professional capacity building, and the overall upgrading of the profession [1]. Reforming education through AI is not only about training specialists who develop AI technologies; it is also about educating planners who can understand, guide, and apply AI and integrate new and established techniques [2].

At the level of values and ethics, attention should extend beyond identifying which planning tasks AI can replace or optimize. It is equally important to ask whether strategies produced through technological integration are timely and effective. Planning support systems ultimately depend on planners' long-term accumulation of theory and knowledge and on their ability to select variables and construct models through appropriate experience. Professional knowledge embodies qualities that distinguish planners from AI and may even enable them to surpass it. Especially when data foundations and computational capacity remain insufficient for a comprehensive digital and intelligent transformation of cities, professional judgment and human-defined standards and regulations retain substantial value. Planning should therefore avoid abandoning all forms of empiricism and sliding into technological determinism [3].

Human planners must also continue to assume responsibility for safety governance, ethical oversight, and humanistic care. AI can be understood as a form of technological democratization: it may shift the organizational structure of planning from a pyramid-shaped power hierarchy toward a more networked, pin-shaped configuration in which planners, decision-makers, managers, and the public all participate in the decision process. The planner's role then moves toward constructing the underlying logic of design, with human needs, emotions, and values becoming the core concern [3].

Although the profession has extensively discussed AI-enabled urban-rural planning, practical applications in core courses such as urban-rural planning and design and principles of urban-rural planning remain limited. This gap makes it difficult to meet the need for educational innovation [3]. To explore the supporting role of AI more deeply, we collaborated with the Department of Electronic Engineering at Tsinghua University to reform the residential area planning component of the core design studio Urban-Rural Planning and Design. The course combines the knowledge-generation and role-playing functions of large models with Grasshopper-based computational design across three stages - preliminary planning, scheme generation, and post-evaluation - and tests a new dual-driven teaching model based on professional knowledge and artificial intelligence.

2 Development of Artificial Intelligence and Its Application in Urban-Rural Planning

2.1 Complementarity between Artificial Intelligence and Professional Planners

Cities are becoming increasingly complex, while the number of stakeholders and the breadth of knowledge involved in urban-rural planning continue to grow, placing demanding requirements on practitioners [4]. Professional planners must master substantial amounts of information, planning tools, and communication skills to understand, analyze, and solve complex urban problems and to balance the interests of governments at different levels, developers, and the public [5]. Conventional experience-based decision-making is increasingly inadequate for these complex urban systems.

AI possesses autonomy, adaptability, intelligent interaction, large-scale data-processing capacity, learning ability, real-time responsiveness, and high levels of integration, giving it considerable potential across many fields. In urban-rural planning, AI has advantages beyond human capacity in storing and analyzing large datasets, identifying patterns, performing calculations and simulations, and generating alternatives. Nevertheless, it remains weak in organizing prior knowledge, establishing value orientations, advancing creative design, producing narrative and aesthetic quality, designing scenarios and experiences, and understanding the deeper logic of human society. It cannot replace professional planners [6].

Professional planners are particularly strong in domains in which AI remains weak: human rules, social values, emotional needs, and experiential qualities. They can use intelligent technologies to generate and iterate planning and design alternatives rapidly and then intervene in, evaluate, and optimize those alternatives under multiple scenarios. In this way, AI can improve efficiency while planning remains people-centered and avoids both uncritical empiricism and extreme technological determinism.

2.2 Application of Large Language Models in Urban-Rural Planning

The emergence of large language models (LLMs), including ChatGPT, LLaMA, Alpaca, and GLM, has expanded the scope of AI applications and strengthened its capacity to handle complex tasks. It has initiated an exponential development of general-purpose AI [7-8], leading some observers to compare LLMs with an industrial revolution. A growing number of researchers have incorporated LLMs into agent-based models to exploit their human-like capacities for perception, memory, reflection, reasoning, planning, and decision-making.

Li et al. [9], for example, introduced LLMs into the simulation of an urban economic system comprising labor, consumption, financial markets, and government taxation. Agents made decisions about employment and consumption that reproduced the classic Phillips curve. Gao et al. [10] developed a social-network simulation system in which agents' emotions, attitudes, and interactions were used to predict the evolution of public opinion and group-level social phenomena, opening new possibilities for research on virtual societies. Park et al. [11] constructed a virtual town of 25 LLM agents on an urban simulation sandbox. The agents communicated, organized parties and elections, worked, and studied; their activities and memories accumulated over time and generated reflections that guided subsequent decisions and behavior.

As research has advanced, the collaborative capacity of LLM agents has received increasing attention. Their ability to understand and generate natural language enables role-playing: after learning from large bodies of text and knowledge, agents can express themselves in different styles and tones, imitate particular people or roles, and perform corresponding tasks. They can solve operations-research problems [15] and undertake software development [16] through pipelines [12] or group collaboration [13-14].

Zhou et al. [17] designed an LLM-agent-based method for public participation in urban-rural planning. Several LLM planner agents guided thousands of resident agents in discussion and repeatedly revised design proposals through negotiation, significantly improving indicators such as ecological landscape quality and public service provision. Yang Tianren et al. [18] proposed a theory and framework for AIGC-enabled urban design and highlighted the advantages of AIGC in learning from large datasets, inference and prediction, generating recommendations, and evaluating and optimizing design. The use of LLMs to learn, retrieve, and evaluate planning texts [19-20] and to construct urban-rural planning knowledge graphs [21-22] further demonstrates their potential as powerful assistants to planners because of their sensitivity to language and context, openness, and generalizability.

3 A Three-Stage Model for AI-Empowered Urban-Rural Planning and Design Education

3.1 Characteristics and Problems of Traditional Core Planning and Design Courses

Urban-Rural Planning and Design is a core course in the planning curriculum and has developed for nearly 70 years since the establishment of the urban planning discipline in the early years of the People's Republic of China. Given the practice-oriented nature of planning, apprenticeship-style studio education offers clear advantages in transmitting practical experience and providing personalized guidance. It also presents major limitations, including delayed knowledge renewal, constraints on students' innovative thinking, strong instructor subjectivity, and the absence of a standardized knowledge system. These problems can be summarized as three deficiencies.

(1) Insufficient scientific and logical reasoning. Current design studios focus mainly on organizing and designing physical space [23]. Their logic is typically guided by functional rationality and visual aesthetics, with limited attention to the economic and social mechanisms underlying spatial formation. Although curricula include economics, sociology, and related courses, these fields are difficult to integrate organically with design studios. Studio work is dominated by drawing; planning dynamics and theoretical rigor are insufficient, and assessment emphasizes the final blueprint rather than the reasoning process and scientific principles [24]. As a result, teaching and evaluation are strongly shaped by individual instructors, with high subjectivity and limited scientific grounding.

(2) Insufficient attention to multiple stakeholders. Traditional design paradigms depend on expert experience and top-down elite perspectives [25]. Within an eight- or sixteen-week studio, students may conduct fieldwork and interviews, but limitations of time, effort, and experience prevent them from understanding the behavior, lifestyles, and interests of diverse groups within the site in sufficient depth. Public participation therefore often remains superficial.

(3) Repetitive work constrains creativity. Across the conventional sequence of preliminary research, scheme design, and drawing production, non-creative tasks consume a substantial share of students' effort. Once a scheme is rejected, students must repeat manual or AutoCAD drafting procedures, which can generate resistance and frustration. Intelligent technologies are urgently needed to replace part of this repetitive work, use AI where it is strongest, and compensate for planners' limitations. This is an important pathway for reforming planning education.

3.2 A Three-Stage Model for AI-Empowered Planning and Design Education

To address the limitations of traditional studio education, we combine artificial intelligence with professional knowledge to cultivate interdisciplinary capabilities. Within limited teaching time, the model helps students conduct social research more effectively, identify the demands of multiple interest groups, and establish a dynamic planning and design process that can be adjusted and optimized continuously through modular professional knowledge. We therefore propose an LLM-enabled, dual-driven three-stage model: preliminary planning -> scheme generation -> post-evaluation. Each stage is supported by LLMs and other intelligent technologies.

3.2.1 Preliminary Planning Stage

The preliminary stage includes planning positioning and user-demand analysis. Professional knowledge supports top-down analysis, including implementation of higher-level planning requirements and reflection on the role and value of the site within the city. In conventional teaching, positioning analysis often becomes broad, comprehensive, and generic, rather than producing a precise site definition at the street and community scale based on residents' needs. Tight schedules and high survey costs also mean that interview samples are incomplete and discussions lack depth, reducing field research to a formal exercise. LLMs can supplement this process from the bottom up by exploring residents' demands for relocation compensation, prospective residents' expectations for spatial layouts and public services, and developers' interests.

During design, we use LLM agents to simulate the stakeholders involved in planning and guide students through multi-agent interaction that approximates public-participation scenarios in real projects. This process deepens their understanding of site positioning and user needs (Figure 1). An agent may act as a resident with specific attributes and express demands for land use and public services; as a knowledgeable government official, it can define planning bottom lines and red lines; as a developer, it can recommend housing products based on the site's development potential; and as a professional planner, it can advise students on design codes and standards.

Prior professional knowledge is essential to these interactions and must be organized systematically into knowledge modules. During field surveys, document collection, and in-depth interviews, students formulate questions based on the predefined modules and pose them to the agents. In this way, they simulate public participation and stakeholder negotiation, quickly understand the demands of different users and the practical logic of project operation, and learn relevant design standards and operating models. After comprehensively reviewing the needs of different agents, students combine higher-level planning requirements with user demands to establish the planning position that underpins subsequent scheme generation.

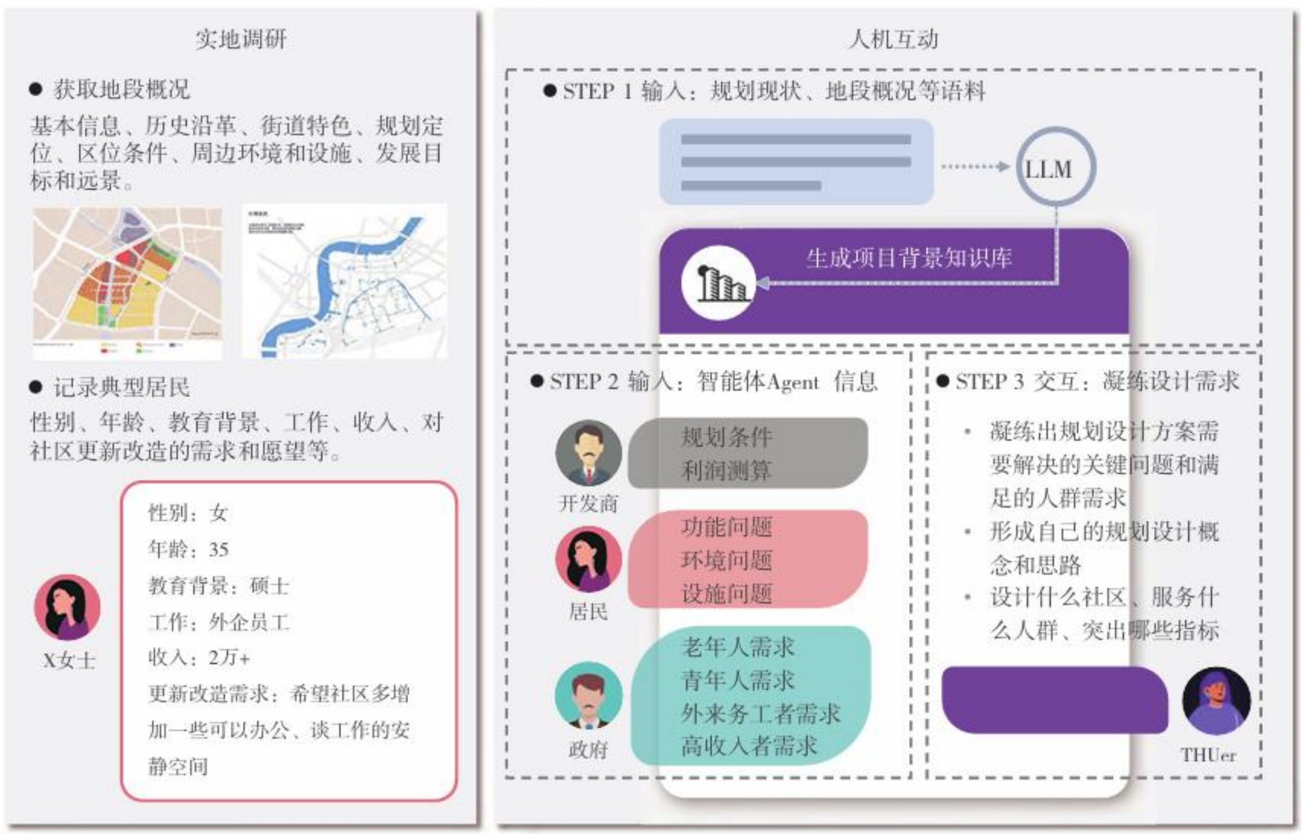


Figure 1. A multi-agent interaction system based on a large language model

3.2.2 Scheme Generation Stage

In conventional scheme generation, students usually prepare several alternatives as hand drawings or physical models, present them, and improve them under instructor guidance until a final option is selected. Two problems are common. First, instructors' recommendations are based on long-accumulated expertise that students with limited professional knowledge may find difficult to understand quickly, sometimes producing resistance. Second, every revision requires repeated drawing, model-making, and indicator calculation, leaving limited time and energy for creative design.

To improve efficiency and enable rapid comparison, Rhino-based modeling and Grasshopper can be used to construct a low-code scheme generator through visual programming. Students enter several types of indicators, and a genetic-algorithm-based generator quickly produces a large number of preliminary massing schemes. The indicators include: (1) non-negotiable constraints, such as site boundaries, land area, land-use type, building setbacks, and solar-access requirements; (2) range-based indicators, such as floor-area ratio, building height, and the proportions of different functions; (3) optimization indicators, such as accessibility to public facilities, views from upper floors, and cost-benefit performance, which are used to compare alternatives; and (4) extension indicators, through which students develop customized metrics and Grasshopper components suited to the characteristics and needs of their own projects.

Before parametric generation, students establish a preliminary planning structure, determine major roads, functional axes, types of public buildings, and housing types, and enter these into Grasshopper. Multiple alternatives are generated under the guidance of the planning position. For a site with exceptional landscape value, for example, landscape optimization may be set as a primary objective. During optimization, students can upload drawings and texts to the multi-agent system at any time. Agents representing government, residents, and developers evaluate the scheme and offer suggestions; students then combine this feedback with the instructor's advice and continue refinement. The integration of LLMs and parametric design creates a continuous feedback loop and reduces arbitrary decision-making. By answering professional questions and explaining their reasoning, agents help students experience the coordination of competing stakeholder interests. Students subsequently select, deepen, and revise automatically generated schemes and add content beyond the reach of the algorithm, including landscape installations, building facades, and public-building design.

3.2.3 Post-Evaluation Stage

Traditional studio evaluation is dominated by centralized instructor critiques, and it is difficult to invite real stakeholders to assess student proposals. Multi-agent-assisted evaluation therefore offers an effective way to combine top-down and bottom-up approaches and to integrate expert and participatory assessment. Instructors can construct an evaluation framework that combines objective and subjective indicators. Objective indicators include calculable measures such as development intensity, the distribution of public facilities, and cost-benefit performance; subjective indicators address aesthetics, comfort, and related qualities.

Conventional assessment often relies on perspectives such as aerial renderings and cannot fully incorporate bottom-up judgments by residents. With LLM assistance, students upload design drawings and texts to the multi-agent system, allowing government, developer, and resident agents to discuss and score schemes from different dimensions, including building arrangement, social interaction and privacy, facility accessibility, comfort, interest, and naturalness. Combined with the instructor's professional judgment, these evaluations produce a final assessment. This not only makes evaluation more engaging but also approximates a real public-participation setting.

The resulting teaching pathway - preliminary planning, scheme generation, and post-evaluation - is shown in Figure 2. Through the dual drivers of professional knowledge and AI, students are guided to identify scientific logic, adopt process-oriented thinking, and solve urban problems in realistic contexts. The learning orientation moves from empirical science, classical theory, and regulatory requirements toward systems science, complexity theory, and evidence-based reasoning. Students learn historical and present-day knowledge from residents, implementation and management thinking from government clients, and cross-sector knowledge from developers and partners. In this way, they identify problems, investigate mechanisms, and respond to needs while recognizing the plural and scientific nature of planning and design.

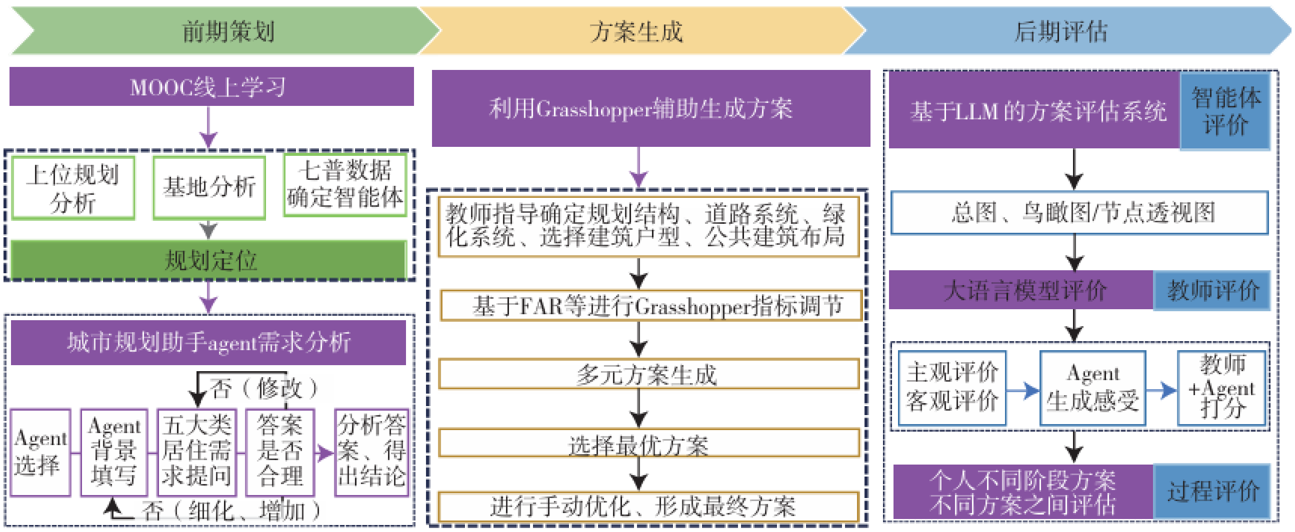


Figure 2. Planning and design teaching pathway: preliminary planning, scheme generation, and post-evaluation

4 Practical Application of the Three-Stage Model in Residential Area Planning and Design Education

The three-stage model was applied to a residential area design studio within the undergraduate design sequence of the Department of Urban-Rural Planning at Tsinghua University. The participants were second-year undergraduate students.

4.1 Preliminary Planning: Positioning and Functions of the Residential Area

The research team developed an LLM-based multi-agent interaction system. During preliminary fieldwork, students recorded, collected, and organized information about the site into textual and visual materials. They also conducted in-depth interviews with representative residents, documented their characteristics, and summarized their recommendations and interests concerning the design project.

On the one hand, hundreds of agents whose attributes matched real-world conditions were generated from census data using conditional probabilities and proportions. On the other hand, information from in-depth interviews with representative residents was also entered into the system. These participants acted as opinion leaders with clearer interests. Text and images were uploaded so that the agents could learn the project's context.

Students could then interact with simulated residents at any time, communicating with people of different ages, incomes, educational backgrounds, and occupations and negotiating with government and developer agents. The teaching team prepared a standardized questionnaire of nearly 60 questions in five modules: housing unit and architectural style, building-combination patterns, roads and traffic, green-space systems, and public-service facilities. Students added questions when necessary and used the dialogue to understand preferences. With human-computer interaction and instructor guidance, they distilled the most important objectives for residential design on a specific site and formulated their own design position (Figure 3).

Figure 3. Refinement of design concepts supported by human-computer interaction

4.2 Scheme Generation Support: Comparing and Selecting Multiple Alternatives

Based on preliminary research and planning, students identified the residential product type and entered basic indicators, including site boundaries, building setbacks, floor-area ratio, spacing coefficients, building height, and unit types. During scheme generation, a low-code generator based on Rhino and Grasshopper helped students produce draft proposals rapidly. Students could also add their own extension indicators. After the system was run, a genetic algorithm generated several massing alternatives, each plotted in a three-dimensional coordinate system whose axes represented building density, floor-area ratio, and other indicators. Students selected suitable alternatives according to their preferences and project requirements for further design (Figure 4). These initial proposals were not complete and still required substantial student input in road organization, landscape systems, and architectural appearance.

The purpose of automated generation is not to replace the cultivation of design ability. By producing many drafts that broadly comply with design codes in a short period, it helps students develop an initial spatial understanding of residential areas and absorb the knowledge embedded in design standards. Creativity is expressed in the planning structure and in detailed refinement. During this process, students continue to interact with agents and respond to questions and suggestions from residents, government, and developers (Figure 5).

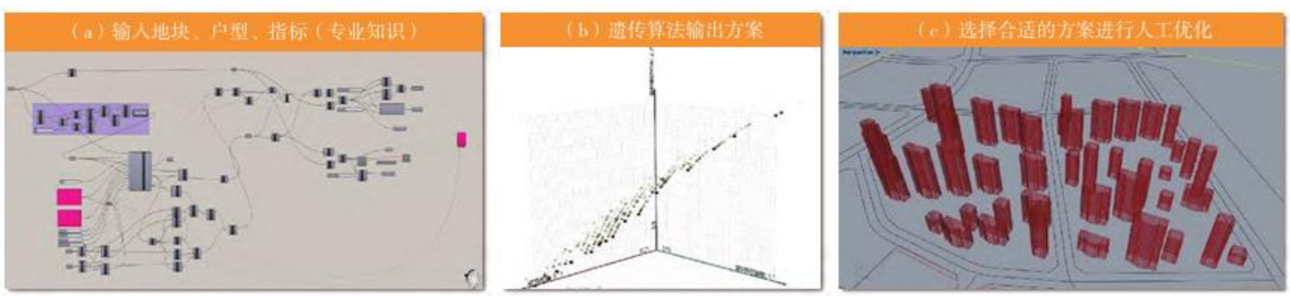


Figure 4. Rapid scheme generation assisted by a genetic algorithm

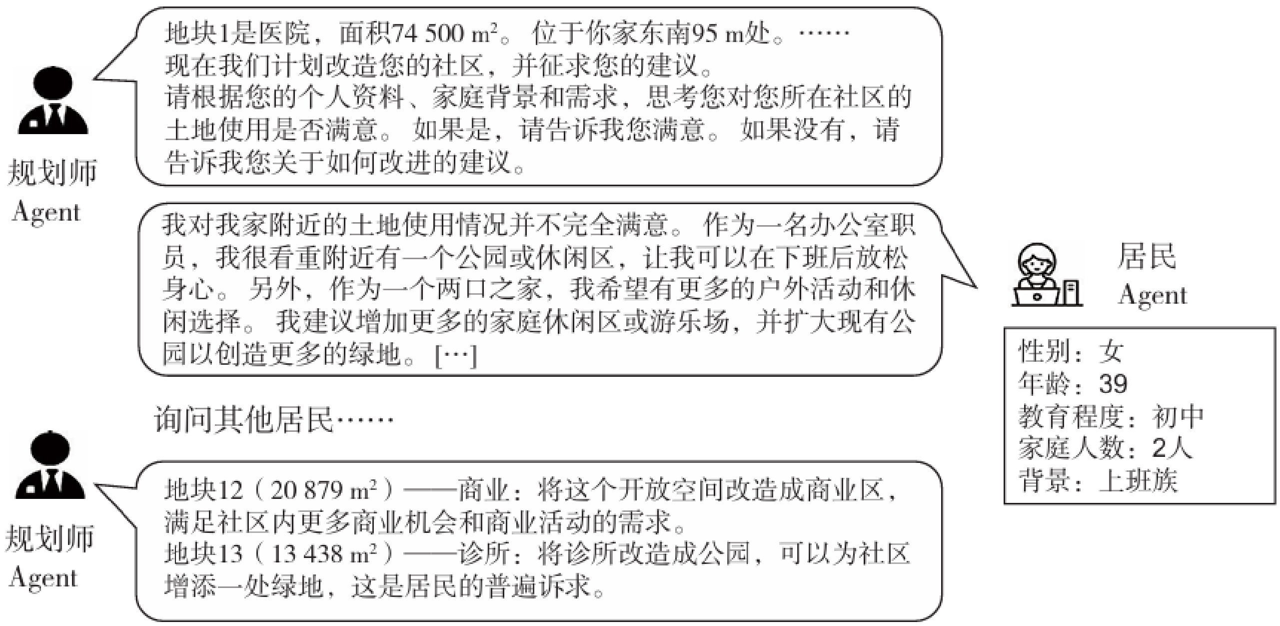
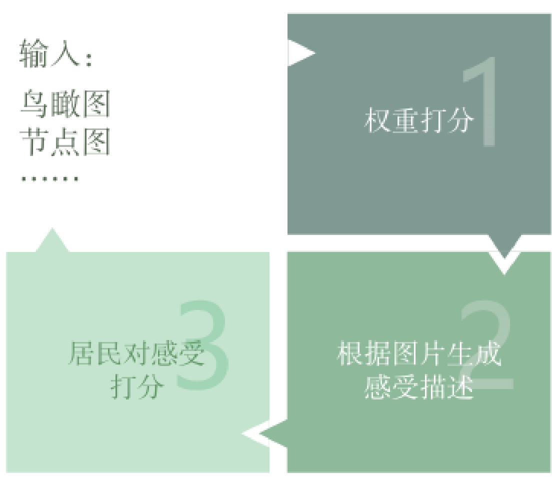


Figure 5. Real-time interaction during scheme development

4.3 Post-Evaluation: Combining Expert and Agent Assessment

At the evaluation stage, students upload their outputs - texts and drawings - to the multi-agent system and enter prompts organized around specified dimensions (Figure 6), allowing different agents to score each aspect of a scheme. Objective indicators, such as service accessibility and green-space coverage, can be calculated, while subjective satisfaction scores can be obtained from virtual government, developer, and public agents. This comprehensive assessment supplements the conventional model in which the instructor is the sole evaluator.

A student can assess the evolution of their own design capacity by comparing outcomes from different stages, while final schemes produced by different students can also be evaluated together to provide an intuitive comparison among alternatives (Figure 7).



PROMPT示例:
请你对图中建筑间距进行评价，5分代表非常满意，4分代表满意，3分代表不一定，2分代表不满意，1分代表非常不满意。请只回答分数，不要包含其他内容。

评价类型	评价指标	非常满意	满意	不一定	不满意	非常不满意
建筑布局评价	建筑间距	5	4	3	2	1
	建筑高度	5	4	3	2	1
	建筑排布	5	4	3	2	1
	交往与隐私性	5	4	3	2	1
公共空间评价	舒适性	5	4	3	2	1
	趣味性	5	4	3	2	1
	交往性	5	4	3	2	1
	多功能性	5	4	3	2	1
	自然性	5	4	3	2	1

Figure 6. Scheme evaluation framework

Applying the three-stage model to residential design education addresses several weaknesses of traditional teaching. First, it shifts attention from physical-space design alone toward the joint satisfaction of spatial and human needs and simulates participatory implementation through virtual public engagement. Second, it strengthens process-oriented design: every adjustment is supported by a corresponding real-world demand rather than by arbitrary intuition. Third, AI reduces repetitive workloads and allows students to devote more time and energy to scientific reasoning, process thinking, and the creative resolution of real problems.

Figure 7. Agent-based evaluation of a student's design outcomes at different stages (top) and final schemes by different students (bottom)

Source: Assignments by second-year students in the Department of Urban Planning, Tsinghua University.

5 Reflections on Urban-Rural Planning Education Driven by Professional Knowledge and Artificial Intelligence

On the basis of the dual empowerment of professional knowledge and AI, we constructed teaching content that combines theoretical knowledge, methods and technologies, and practice-based improvement. The course focuses on real planning and design situations and enables students to understand policy systems and the interests of multiple stakeholders. With intelligent technologies as support, it cultivates combined capabilities in theory and technology, including data analysis, planning research, and prototyping, while developing creative, systemic, and people-centered thinking.

This approach replaces a one-way model in which instructors transmit knowledge and students passively receive it. It encourages independent exploration, increases classroom participation and students' sense of achievement, and improves the efficiency of knowledge transfer, skills training, and design feedback. Teaching, learning, the system, and users thus become mutually reinforcing.

5.1 Professional Knowledge and Competence Are Preconditions for AI-Empowered Planning Education

Although AI demonstrates certain capabilities in planning, professional work spans multiple dimensions: understanding space, environment, and social needs; identifying residents' emotional demands; maintaining sensitivity to social change; and exercising creativity. These remain difficult for AI. Even in quantitative analysis, where AI is comparatively strong, conclusions may be meaningless without guidance from professional knowledge [26].

The present teaching experiment shows that instructors must organize and explain knowledge points throughout the entire sequence of preliminary planning, scheme generation, and post-evaluation before using LLMs to support understanding. In the preliminary stage, key knowledge of residential design is converted into a question bank, supplemented by student-generated questions, and posed to different agents to obtain a comprehensive picture of bottom-up needs and support planning positioning and functional layout. During generation, students must first determine the road layout and open-space framework before using Grasshopper. Finally, the evaluation framework is constructed according to the students' predefined planning objectives, and LLMs are used to assess schemes and deepen understanding of residential design principles.

5.2 AI-Empowered Design Education Can Improve Scientific Literacy and Design Quality

AI-assisted residential design education contributes in three main ways. First, in positioning and demand analysis, conventional practice relies largely on designers' subjective judgments, whereas role-playing agents enable an analysis of a much broader sample of relevant groups. Second, in scheme generation, different planning objectives - such as landscape optimization or maximum accessibility to public services - can be used to generate multiple spatial alternatives for selection. Third, once students have optimized a proposal, agents evaluate it against the position and objectives established in the first stage. Combined with professional instructor judgment, this produces a more comprehensive account of strengths and weaknesses, compensates for the limitations of experience-based assessment, strengthens scientific literacy, and broadens understanding of schemes from the perspectives of different stakeholders.

5.3 Integrating Professional Knowledge and Artificial Intelligence Is Essential to Educational Innovation

The residential design experiment demonstrates that neither professional knowledge nor AI should be neglected. They must cooperate closely and complement one another in their respective areas of strength. Every stage of the three-stage model embodies this dual drive: instructors teach professional knowledge;

students internalize it and translate it into dialogue with large models; planning objectives then guide generative design; after human refinement, large models support evaluation.

Overall, AI should be treated as a tool rather than a substitute for planning education. It can assist students with selected tasks, but final design decisions and creative outputs still depend on professional judgment and experience. AI is more likely to transform how students work than to replace them. Planning students therefore need to adapt to emerging technologies and use AI to improve efficiency and creativity.

6 Summary and Discussion

Urban-rural planning and design education driven jointly by professional knowledge and artificial intelligence is an emerging educational model intended to provide a comprehensive, in-depth, and practical learning experience. It seeks to improve design and innovation ability, technological application, critical thinking and analysis, teamwork, and communication, thereby preparing students for future professional development.

In this residential design experiment, a cross-disciplinary teaching team from the Department of Urban-Rural Planning and the Department of Electronic Engineering at Tsinghua University, together with iFLYTEK, developed intelligent teaching products and evaluation tools to support students' planning work. The teaching results show that an interdisciplinary team is essential: it can resolve professional and technical problems quickly and help students build a comprehensive understanding of residential area planning and design.

Two misconceptions should be avoided. The first assumes that AI can generate large numbers of schemes rapidly and therefore dominate planning and design. The second clings to traditional apprenticeship teaching and rejects advanced technologies. Wu Zhiqiang et al. [27] identified three typical modes of smart-city development: the technology-provider-led T mode (Technology Mode), the D mode oriented toward solving actual demands (Demand Mode), and the formalistic E mode (Exhibition Mode), which advances through showrooms without being integrated into real urban operations. The E mode can consume substantial resources, become detached from daily needs, and prove unsustainable.

AI-enabled planning education must not become a display of technological sophistication that forgets the original goal of residential design teaching - mastery of theories of the living environment and comprehensive design skills. Professional knowledge and competence remain indispensable. At the same time, advanced methods should not be rejected. AI can deepen students' understanding of the social forces and roles involved in residential design, including government, developers, residents, and planners, and can expand their scientific literacy.

The experiment also faces limitations. Team-based project practice and interdisciplinary learning under instructor guidance place high demands on teachers' knowledge backgrounds and cross-disciplinary vision. Determining what AI can and cannot do in design education itself requires continuous experimentation, making technical support from an AI team essential. Students who have not yet acquired the fundamentals of residential design may obtain little value from dialogue with large models, so instructor guidance and repeated attempts are necessary. Moreover, learning Rhino modeling and Grasshopper visual programming requires additional time and effort, which makes group work more effective. Intelligent teaching tools, question banks, and case libraries should be expanded further to create transferable teaching resources that enable students to master AI methods within a short period.

In general, the central challenge facing traditional planning education is how to adapt to rapidly changing technologies and professional needs. The way forward is to respond proactively, renew teaching content and methods, and cultivate future competitiveness and lifelong learning. Students should be encouraged to cross traditional disciplinary boundaries, integrate knowledge and skills from different fields, develop innovative thinking, and strengthen their capacity to solve complex problems in the new technological era.

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