Urban Design Assisted by New-Generation Artificial Intelligence: Paradigm Transformation and Digital Intelligence Empowerment

LIU Yibo, WU Zirong, SUN Cheng

Abstract: The interdisciplinary field of urban design, which bridges urban planning and architecture, is at an early stage of theoretical development and technological exploration, advancing alongside the emergence of a new generation of artificial intelligence. From a design process perspective, the filed primarily faces the challenge of reconciling value rationality and instrumental rationality. In this context, it is necessary to strengthen the cognitive depth and operational scope of urban design through paradigm and digital intelligence empowerment respectively. In terms of value rationality, urban design practice needs to be transformed from a holistic and value-centered approach to an interactive one, achieved through reconstructing operational mechanisms, reshaping value systems, and reorganizing spatial features. In terms of instrumental rationality, it is crucial to transform the digital intelligence in urban design from a data-driven model to an AI-driven one through exploring pathways to incorporate cross-domain technologies, such as artificial life forms, blockchain, and AI-powered image and video generation models. In addition, future-oriented urban design should uphold the purpose of technological development, which should assume auxiliary rather than dominant roles in addressing human needs, enabling effective and full life-cycle management of human settlements.

Keywords: new-generation artificial intelligence; urban design; paradigm transformation; digital intelligence empowerment

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Artificial intelligence (AI) is progressively permeating and profoundly reshaping social life. With breakthroughs in key technologies and the accelerated construction of emerging application scenarios, technology-enabled development has become a defining feature of high-quality growth. AI has emerged as an important driver of Chinese modernization and is increasingly transforming the elemental systems and operating mechanisms of architecture and planning[1].

Since AI entered the field of urban design in the late twentieth century, digitization and informatization have gradually become important supports for the discipline. Technologies such as virtual reality[2] and computer vision[3] provide high-precision, high-volume data for urban analysis. On this basis, functions including element interpretation[4-7], development simulation[8-12], decision generation[13-14], and implementation evaluation[4,15-17] support the prediction and execution of urban sustainability objectives[18] and further advance ecological protection, economic growth, and social justice[19-22]. Existing studies[23-24] have productively explored AI-based identification and simulation of population and spatial development patterns, as well as the assessment of facility-location impacts. These efforts have generally achieved more precise pattern discovery and more scientific system construction, partially satisfying core planning and design needs in urban data analysis, development simulation, spatial-structure optimization, and functional allocation. The influence of new-generation AI on urban design is now beginning to emerge, but current research remains at an early stage of theoretical construction and technological exploration. Forward-looking inquiry and systematic design that diagnose existing problems and use new AI technologies to break through them have therefore become an inevitable direction for innovation in urban design.

1 Dilemmas: Real-World Paradoxes in the Development of Urban Design

As an interdisciplinary field connecting urban planning and architecture, urban design is characterized by creativity, the integration of reason and emotion, human-centeredness, and spatial concreteness[25-26]. This section analyzes the development of urban design under the influence of AI and its corresponding characteristics, identifies the paradoxes emerging across the design process under new-generation AI, and distills the current challenges of value rationality and instrumental rationality.

1.1 The Development of Urban Design under the Influence of AI

Closed-model genetic algorithms[27] and microwave integrated optimization design[28] were already being applied in biology and industrial manufacturing by the mid-twentieth century. They entered urban research only around the turn of the century, however, and their functional positioning remained unclear. Urban design therefore lagged behind other fields in both theoretical development and technological adoption. Under the influence of AI, urban design has successively passed through a computer-aided design (CAD) stage, in which early AI primarily served as a drafting tool; a parametric design (PD) stage, in which computer-based AI became a tool for dynamic urban modeling; and an algorithms-aided design (AAD) stage, in which automated AI assisted analysis and judgment. As shown in Fig.1 and Tab.1, a preliminary theoretical, methodological, and technological system for AI-assisted urban design has taken shape[33-35], while its comprehensiveness, practicality, innovativeness, and scientific rigor continue to improve with advances in related research and practice.

In recent years, increasingly complex and uncertain urban ecosystems and policy environments have made urban design tasks more demanding. Yet urban research still suffers from discontinuities between design stages, high knowledge intensity, and substantial costs[32]. Innovation at the output end of planning and design, together with stronger feedback between planning, design, and spatial governance, has therefore become urgent. Although new-generation AI represented by large language models such as ChatGPT and image generation models such as Stable Diffusion remains at an early stage of technological development, its capacity to integrate massive, high-dimensional, multisource datasets, together with its potential for self-training and adaptation, scientific rigor, and interpretability, indicates the prospects of artificial intelligence-generated design (AIGD)[36]. AI-driven urban research responds to the new technological wave and directly addresses the innovation and transformation needs of architecture and planning.

AI is now widely recognized as a key technology supporting urban design. Nevertheless, major questions remain unresolved regarding how its new generation will transform urban space and the operation of spatial elements, and how it will affect research and practice in urban planning, particularly urban design.

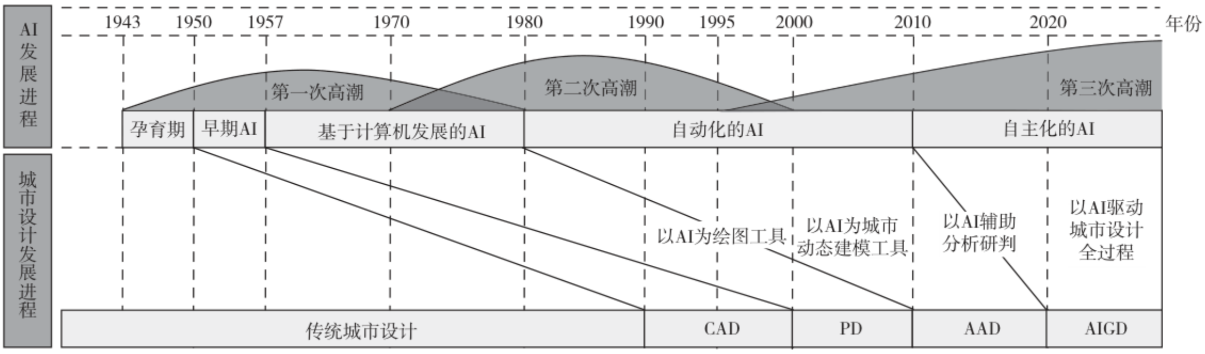

Fig.1 The relationship between AI and urban design

Tab.1 The development of urban design under the influence of AI

城市设计进程	发展时间	AI工具	城市设计发展优势	城市设计发展问题
CAD	20世纪末21世纪初	早期AI	借助以CAD等计算机绘图软件为代表的AI传达设计方案[29]，主要使用勘测调研、问卷调查等田野调查法获取城市空间数据	设计数据精度较低，设计要素单一，设计空间大多仅停留在人视角下建筑和场地空间的功能和美学层面，设计工作单向传导，繁重低效，且存在与城市规划、城市治理逻辑分离
PD	2000年至2010年	基于计算机发展的AI	通过AI提供的描述城市情境的参数化工具和可将参数化工具与城市社会经济数据进行空间融合的设计平台，构建城市多元性能的量化指标体系，建立短期时间演变下的城市立体模型，使构想经济效益达成最优解的空间方案成为可能	由于计算、存储能力限制，基于计算机发展的AI离识别与获取高精度、高产量、高质量数据尚有一段距离，此外城市动态模型建设成本极高，在城市设计中的普及性和实施性不强，相当一部分城市设计仍以质性研究为决策依据[30]
AAD	2010年至2020年	自动化的AI	利用自动化AI，突破CAD等绘图软件和BIM等3D建模软件的局限性，学习城市系统要素特征的能力，结合专家决策预测城市系统发展、提出风险防控决策和监督系统运转[31]	由于AI尚未形成基于城市规划建设理论研究和实践经验的城市空间认知，其设计决策输出质量不高，且设计师需在该过程中投入大量时间成本，因此城市多方利益主体对其智能决策模型的实施性仍保持观望态度[32]
AIGD	2020年至今	新一代自主化的AI	具备海量高维度多源数据集成能力、自训练和自适应潜力、科学性和可解释性	

1.2 Real-World Dilemmas in Urban Design

The typical urban design process can be summarized as problem formulation, design-scheme development, scheme evaluation, scheme decision-making, and problem resolution[25]. Diversified data sources and increasingly intelligent human-machine integrated platforms under AI compensate for deficiencies in existing tools for urban-design decision-making and creation. At each stage, relevant technologies can process, analyze, simulate, and present urban-design data models, improving efficiency, solving design problems, and enhancing design quality. It is widely accepted that new-generation AI will transform the entire urban-design process[15,23,26,37-38]. The principal current dilemmas are shown in Fig.2.

(1) At the stages of problem formulation and scheme development, a paradox exists between the incomplete cognitive system of AI models and the multidimensional, multi-perspectival development of urban space. The limitation of AI cognition appears at two levels. First, current design models emphasize optimizing the economic competitiveness of urban space, while paying insufficient attention to non-material urban information such as historical context and design aesthetics that cannot be captured by data sensors. Some studies have developed methods combining quantitative and qualitative indicators, but these remain preliminary, are generally limited to single-element design, and have not yet been applied to complex urban scenarios; research on multiscale three-dimensional

design is still limited. Second, AI innovation is inherently interdisciplinary, while urban design involves multiple stakeholders. These conditions place higher demands on AIGD knowledge graphs and integrated models. Defining human-machine relations and disciplinary positioning, constructing multilevel AI-assisted platforms with heterogeneous multisource data, integrating cross-sector knowledge, and establishing AIGD mechanisms that combine different algorithms and generative processes have therefore become important tasks.

(2) At the stages of scheme evaluation and decision-making, a paradox exists between the binary logic of AI decisions and the plural complexity of urban-design content. Most AI-related methods remain at the conceptual or experimental-validation stage and focus on improving the intelligence of design models and platforms. Yet intelligence level is not equivalent to design decision-making capacity. Intelligence is mainly manifested in calculation and decision speed and in multithreaded problem processing, whereas the multidimensional, engineering, and social nature of cities requires multi-objective evaluation of complex scenarios. Stronger connections between AI research and design creation, together with improved technological generalization, are therefore necessary. Moreover, AI decision systems operate differently from urban stakeholders. Their spatial interpretations can diverge from actual urban conditions, and their binary, black-or-white decisions may result in insufficient ethical consideration, spatial injustice[39], or outcomes detached from reality.

Overall, the characteristics of AI development, urban systems, and urban-design logic indicate that urban design oriented toward new-generation AI must resolve two fundamental dilemmas.

(1) The dilemma of value rationality. AI is developing rapidly, but its operating logic cannot yet be fully reconciled with urban-design mechanisms. Cognitive and decision-making limitations in urban design ultimately reflect the still-unclear distribution of rights and responsibilities among the multiple actors involved in AI operation. This issue will determine the ecology of AIGD development: the extent to which AI technology is integrated with designers' work, urban-design tools, and urban governance, and ultimately the validity and enforceability of design decisions. At the level of value rationality, urban design must extract new paradigm characteristics and transformation requirements from the application of new-generation AI.

(2) The dilemma of instrumental rationality. The interdisciplinary trajectory of AI, the social content of cities, and regional differences all impose technical demands for customized spatial design. At present, AI cannot construct a comprehensive digital-intelligent model covering the full urban system, and the practical value of generated schemes remains limited. This constrains market and public participation in AIGD, restricts the scale of industry application, and ultimately weakens the momentum and rational realization of AIGD. At the level of instrumental rationality, urban design must clarify the logic of digital-intelligence empowerment from data-driven to AI-driven development.

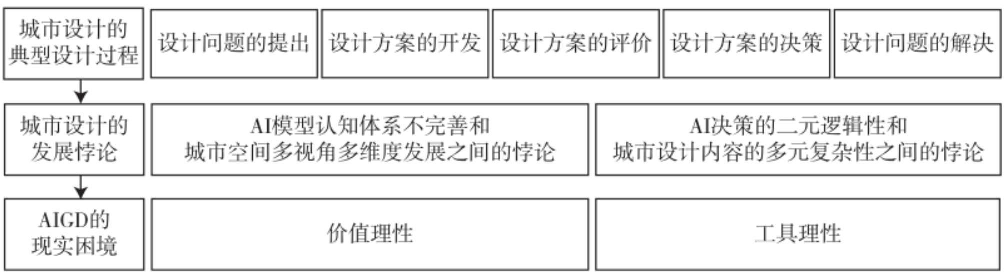

Fig.2 The practical dilemma of urban design

2 Paradigm Transformation: From Single-Mode to Hybrid Design

To realize value-rational urban design in the era of new-generation AI, the direction of paradigm transformation must first be interpreted. According to the nature of human-machine relations, the evolution of urban-design paradigms can be summarized as a progression from a holistic paradigm, to a value-oriented paradigm, and then to an interactive paradigm. This entails a shift from subjective design conducted solely by the human mind without AI, to an objective paradigm in which parametric models and algorithms assist computer-based decisions, and ultimately to a hybrid paradigm of future human-machine interaction. The transformation involves the reconstruction of mechanisms, the reshaping of values, and the reorganization of design space.

2.1 Reconstructing the Transmission Mechanism

During the PD and AAD periods, the powerful data-storage and computing capabilities of computers attracted considerable professional attention. Urban design became strongly data-supported, and its transmission mechanism took the form of a one-way “computer-space-human” structure. Designers passively received and refined the urban data-analysis, monitoring, and prediction models provided by AI. On the one hand, this accelerated the conversion of urban spatial cognition from qualitative description into quantitative information incorporating historical and multiscale evolution and capable of dynamic updating. On the other hand, it encouraged outcomes that reduced diverse urban interests to economic competitiveness, treated urban space as a purely quantified physical environment without humanistic concern, and regarded planning and design as maintenance of urban data-system failures.

As AI technology advances, urban design will increasingly emphasize the semantic logic of AI systems, concrete spatial anchors, and implementation through collaboration with designers in order to ensure controllability. Building on the strengths and limitations of previous mechanisms, a ternary, reciprocal “human-AI-space” structure is proposed (Fig.3).

Designers will shift from being drafters and planners to becoming experts in design experience and logic and creators of design schemes. They must provide AI with design experience and promptly verify and optimize its cognition, model operation, and implementation. Administrative authorities should establish AIGD standards and value orientations and organize regular supervision and evaluation of urban-design models and outcomes. The public should update its understanding of AI and AI-driven design results, express needs, and offer supervisory feedback through AI-mediated transmission. New-generation AI interprets acquired design logic and schemes through specific parameters and generates idealized urban-design models as preliminary feedback. Urban space, in turn, serves as the real-world reference for AI self-training and adaptation, allowing spatial cognition to develop both vertically and horizontally and to combine subjectivity with objectivity, while design systems integrate design sensibility with scientific rigor and functionality with humanistic values.

This ternary structure breaks the deadlock of passive design and clarifies that AI is fundamentally shaped by cities and people, giving AIGD strong internal connectedness and developmental capacity. As a complex system that shapes social dynamics, the city does not passively accept AIGD. Rather, it reshapes material space through environmental behavior under urban design, while its spatial elements and data provide the raw materials and momentum for AI and influence the very nature of AI[40].

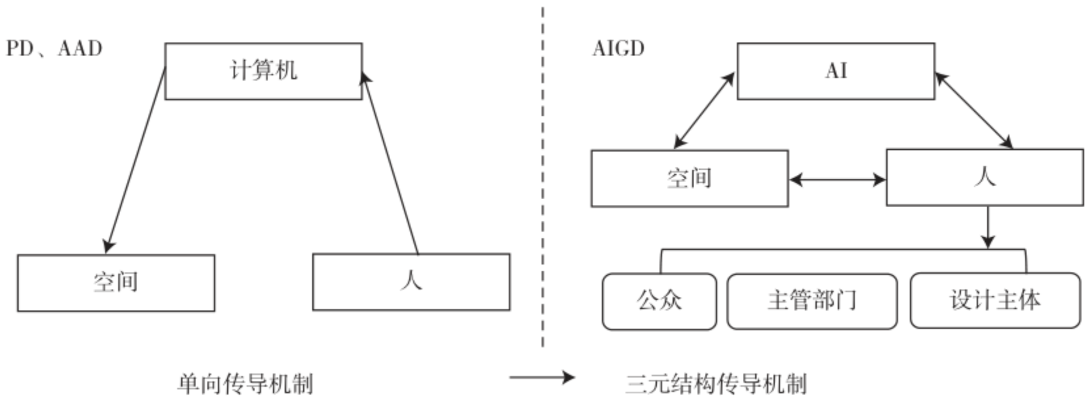

Fig.3 The rationale for reconstructing the conduction mechanism of AIGD

2.2 Reshaping Human-Centered Values

People are both core structural elements and driving forces of cities and AI, as well as the starting point for defining urban-design problems and the subjects that perceive design effects. AI-assisted design, construction, and supervision must ultimately be completed by people, and the resolution of design problems directly or indirectly affects them. PD emphasized quantifying the public interest and treated stakeholders as ideal economic agents. AAD further incorporated human-centered thinking and positioned people as natural persons. With new-generation AI, urban design must clarify human-machine relations and reshape design values in accordance with the working characteristics of human and machine intelligence and the developmental needs of society and individuals.

In design decision-making, the human mind combines limited computing capacity with the integration of reason and emotion. AI has relative advantages in urban perception, learning efficiency, and knowledge linkage because of its powerful computing and storage capacity, but it lacks an established cognitive foundation for urban design and genuine creative ability[41]. New-generation AI can capture high-precision, multidimensional spatial data and human-perception information. It is therefore a material extension through which people can investigate urban operating laws and design needs, and one of the productive forces of human-led urban design. In relation to the natural environment, people are understood through the spatial articulation of social and natural attributes; in relation to the social environment, the rights, responsibilities, and supervision of all parties in the division of urban-design labor are more clearly defined. New-generation AI thus enables the integration of the ecological person and the natural person in urban design (Fig.4).

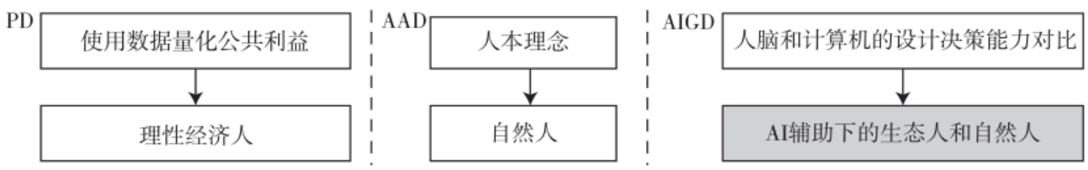

Fig.4 The rationale for redefining the humanistic values of AIGD

2.3 Reorganizing Design Space

Because urban design creates spatial order, the paradigm empowered by new-generation AI will ultimately be expressed through a reorganization of design space. This process occurs at the macro, meso, and micro scales (Fig.5).

2.3.1 Macro Scale: An Urban-Design Development System Integrating Hard and Soft Dimensions

At the macro scale, AIGD can generate a spatial-development model linking hard and soft dimensions by combining material-space construction with humanistic development. Hard urban design focuses on updating spatial functions, maintaining normal infrastructure services, supporting basic production and everyday life, and strengthening spatial resilience. Soft design emphasizes the continuity and expression of natural resources, history and culture, and morphological identity, allowing urban space to retain traces of growth, embody public participation in urban history, and enhance humanistic value and belonging.

2.3.2 Meso Scale: An Intelligent Organizational System for Organic Urban Clusters

At the meso scale, urban-design space empowered by new-generation AI will exhibit the intelligent logic of complex organic clusters. Previous AI applications encouraged rationalized urban design and facilitated urban operation and management, but also constrained the spatial potential of functional clusters[42-43]. New-generation AI can construct virtual urban spaces at real-world scale, calculate possible organic combinations of urban elements according to urban activities, simulate organizational modes, summarize spatial-design requirements arising from self-organizing urban activity, and supervise implementation. This enables clusters to become units for cultivating spatial vitality and functional resilience and supports more intelligent and organic urban development.

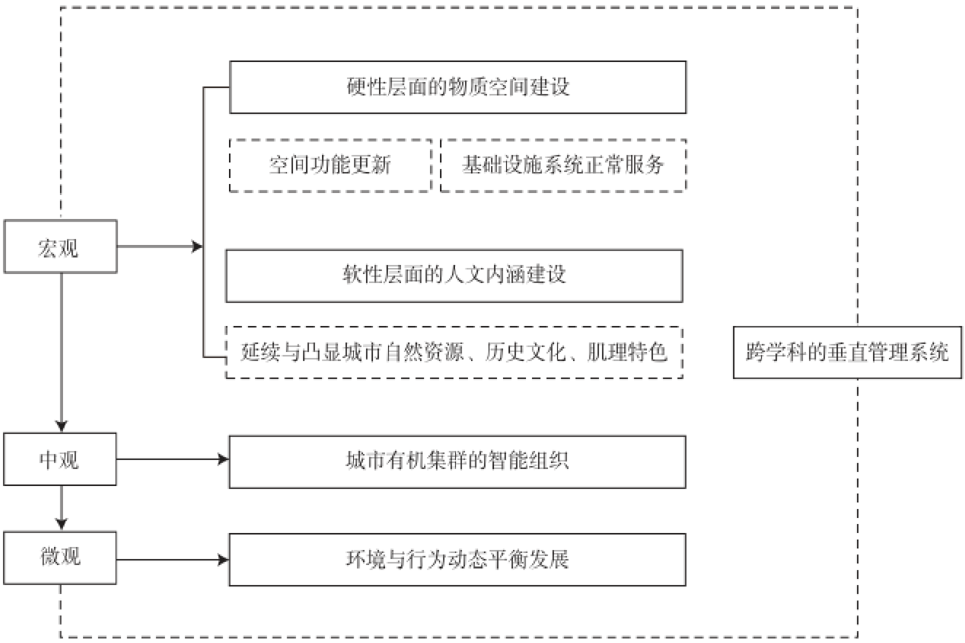

Fig.5 The rationale for reorganizing design spaces of AIGD

2.3.3 Micro Scale: A Spatial Medium for the Dynamic Balance between Environment and Behavior

At the micro scale, urban design assisted by new-generation AI will focus on the concrete operating mechanisms of organic urban clusters - the logic and reciprocal influence of place and behavior - and use them to maintain a dynamic balance between environmental and behavioral development. Low greening rates, high population and building densities, monotonous urban fabric, and mismatches between urban scale and spatiotemporal activity can generate negative emotions and reduce activity efficiency. Conversely, increasing rates of negative behavior can reduce the efficiency of spatial use and undermine productive performance, facility sharing, and the openness of public space. New-generation AI can identify the spatiotemporal specificity of relationships between human behavior and the urban environment and assist designers in producing refined, human-centered spatial interventions.

A vertical urban-design management system can additionally maintain organic order from the macro to the micro scale, dynamically quantify the effects of each level, and monitor implementation. Overall, the massive data-storage capacity and highly integrative interpretive ability of new-generation AI support integration and extension across macro, meso, and micro levels, together with unified and realistic visualization, thereby deepening and broadening urban-design cognition and implementation.

3 Digital-Intelligence Empowerment: From Data-Driven to AI-Driven Design

The transition from CAD and PD to AAD and AIGD has been driven by technology. The earlier stages primarily strengthened spatial analysis and dynamic monitoring through data. As more intelligent human-machine integrated platforms continue to emerge and evolve, urban design has begun to explore AI-driven technologies in three principal directions.

First, in relation to physical mapping, urban intelligent models create new possibilities for representing urban characteristics. Digital twins, for example, use virtual reality, machine learning, and related technologies to obtain real-space data by tracking and identifying dynamic information, establishing real-time links and feedback between physical and digital cities.

Second, in relation to simulation and prediction, intelligent simulation technologies provide analytical pathways for multivariate information games and dynamic optimization. As AI strengthens the simulation and predictive capacity of urban intelligent models, a growing body of research has addressed population size, land growth, traffic flow, and related phenomena[19,21-22,44].

Third, in relation to precision design, generative design supported by deep-learning and machine-learning algorithms provides technical assistance for implementation in complex built environments. Studies have used AI to explore spatial interaction design and design decision-making, building interactive design platforms through the generation and design of spatial-visualization models and thereby supporting precise interventions.

Although design remains largely data- and algorithm-driven, medicine, biology, and mathematics have taken the lead in exploring new-generation AI[45]. Their pathways for combining cross-disciplinary technologies with AI offer technical references for genuinely AI-driven urban design and for overcoming the dilemma of instrumental rationality. Three broad pathways are particularly relevant.

3.1 AI + Artificial Life

Current AI remains largely confined to intelligent operations in individual domains such as image recognition, speech recognition, and dialogue response[46-47]. New-generation AI seeks coordinated whole-brain functions, including self-understanding, self-control, self-awareness, and self-motivation. Brain-intelligence (BI) learning models combine artificial life (AL) and AI, using not only neural-network structures and parameter-optimization mechanisms[48] but also genetic models such as gene regulatory networks (GRNs) and evolutionary reaction networks (ERNs)[49]. These models address limitations of deep learning, including the inability of self-training models to operate multiple tasks simultaneously and the inability to adapt learned outcomes across disciplines and domains, allowing AI to operate autonomously and efficiently even in unsupervised environments. Brain intelligence may also establish associations between elements that appear only weakly related, in a manner similar to the human brain[50]. Although BI learning models currently remain largely theoretical in medicine and biology, their logic offers a useful reference for reciprocal information exchange between AI and designers in urban design.

3.2 AI + Blockchain

AI provides urban design with diverse and highly precise data, but it has not yet developed reliable capabilities for cleaning, screening, accurately interpreting, and protecting assets on the basis of urban-development experience[51]. This increases the costs of data analysis and scheme implementation and also poses potential risks to urban development, territorial space, and even national defense. To create secure, unstructured data-management models, public health and communications research has combined blockchain and AI. Blockchain's highly accurate, decentralized storage and encryption can improve the replicability, associability, and security of AI data storage and enable autonomous data cleaning and use based on data characteristics[52-54]. Such integration can support the high-quality acquisition and asset control of data across multiple urban spaces and even regional space. Although currently applied primarily to medical and financial data storage and statistics, it has considerable potential to improve the efficiency of extracting, accessing, and protecting urban spatial data.

3.3 AI + Image and Video Generation Models

For the representation of urban-design concepts and schemes, text-to-image models such as DALL-E[55-56] and text-to-video models such as Sora[57] overcome the tendency of GAN-based training models to fail[58]. Through multimodal training and adaptation involving text and images, they support the construction of design imagery, the reproduction of the real physical world, and the simulation of design schemes. In essence, image and video generation models reorganize fragmented multimodal knowledge structures, simulate and extend the material operating rules of physical space, and expand human thought and vision. On the one hand, they provide diverse interpretations of complex urban-design contexts and shift designers from passive recipients of data to active producers of schemes. On the other hand, they expand the design object from spatial imagery to complex regional and urban environments, thereby optimizing the organic order of regional production and everyday life.

4 Conclusion and Outlook: Urban Design for the Future

The dilemmas of value rationality and instrumental rationality under AI create both opportunities and necessities for paradigm transformation and digital-intelligence empowerment in urban design. Overall, resolving the challenges of new-generation AI-driven urban design requires returning to the original purpose of technology, clearly defining AI as an auxiliary rather than a replacement from the perspective of ethics and safety, and ultimately realizing full life-cycle management of human settlements.

4.1 Essence: Returning to the Original Purpose of Technology

Regardless of how far AI technology advances, its application in urban design must remain guided by the discipline's original aims. AIGD can emphasize mutual benefit and symbiosis between people and urban space through four measures: ① constructing AI value logic and technical frameworks that strengthen multimodal self-training while preserving designers' autonomy; ② extracting urban spatial data and refining design objectives on the basis of design experience, existing spatial problems, and the developmental needs of cities and communities; ③ simulating designer-customized schemes to anticipate spatial risks and identify optimization priorities; and ④ optimizing design schemes and practice by integrating spatial perceptions expressed through public participation with the construction experience of urban designers.

4.2 Ethics: Assistance Rather than Replacement

AI development aims to improve the multi-scenario adaptability of self-training models, increase storage and computing capacity, and strengthen self-control and self-supervision. It cannot and should not replace designers. Urban-design schemes evolve with human development and deepen through the relationship between urban environments and human behavior. Because AI is not itself a stakeholder in urban space, it cannot directly perceive spatial effects or autonomously renew spatial cognition and technology; it can only assist designers in expanding and converging their thinking. Even with AI and high-capacity data, designers should not depend excessively on data analysis and generative design. They should instead use intelligent tools to extract professional experience more efficiently, produce forward-looking design concepts, and integrate people-centered empowerment with technological empowerment.

4.3 Contribution: Full Life-Cycle Management of Human Settlements

New-generation AI can simplify the operating framework of urban design and improve the predictability and controllability of spatial elements. Digital-twin models capable of simulating movement through time and space can screen and compare distinctive phenomena in human settlements; AI-customized schemes can improve the scientific rigor and diversity of design decisions; machine learning can construct diverse self-learning frameworks for urban space, strengthening generalization and implementation; and collective-intelligence governance can dynamically supervise implementation through the concept of symbiosis among multiple life forms. With new-generation AI as a platform, urban-design operating mechanisms and spatial data models can connect and integrate information and development, ultimately enabling refined full life-cycle management of human settlements.

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