Digital Planning Technology: Data and Knowledge

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Abstract: This paper provides a systematic overview of digital planning technology, in particular, its scope, types, frontier trends, and main obstacles viewed through a data and knowledge-driven technological paradigm. Firstly, it distinguishes between the two concepts of digital technology and digital planning technology. Secondly, it summarizes two technological paradigms, driven by knowledge and data respectively, based on an overview of the evolutionary paths of three types of digital planning technologies: urban modeling technology, spatial-temporal big data planning technology, and artificial intelligence planning technology. Lastly, the paper discusses frontier trends in digital planning technologies from the perspectives of data and knowledge. It is concluded that digital planning technologies can be understood as digital applications in planning analysis, simulation, and decision-making throughout the planning processes. The specific application is determined by either the data- or knowledge-driven paradigms. While the former better supports planning analysis and simulation, deficiencies in the latter hinder decision-making. Future digital planning technologies are expected to be driven by both data and knowledge. The challenge lies in the transition from data to knowledge through data-based learning, extracting the "white-box knowledge" in planning, and allowing knowledge to drive analysis, simulation, and decision-making in planning.

Keywords: digital planning technology; digital technology; data-driven; knowledge-driven; technological paradigm

In the current digital era, digital technologies are profoundly changing people's lives and work. The development of cloud computing, big data, artificial intelligence, and other digital technologies has accelerated the digital transformation of society, including daily life, the economy, and governance. The field of urban and rural planning has also felt the strong impact of digitization and digital technologies. The past decade has been a period of tremendous influence from digital technologies on urban and rural planning. For example, digital twin technology and virtual reality technology have changed the way we perceive and explore urban spaces [1-2], while spatiotemporal big data, artificial intelligence, and other technologies have rapidly integrated into urban and rural planning research and practices [3-5]. The rapid rise of Artificial Intelligence Content Generation (AIGC) technology is changing the way planning drawings and reports are generated. From the supporting technologies of planning research to the generation of outcomes in planning practices, digital technologies have had a comprehensive and significant impact on urban and rural planning.

The past decade has also been a period when the urban and rural planning discipline focused heavily on digital planning technologies. Spatiotemporal big data and artificial intelligence technologies have become hot topics in the field, sparking two waves of interest. Since the early 2010s, spatiotemporal big data technology has attracted widespread attention and had a profound impact on urban spatial research. Spatiotemporal big data technology has been rapidly applied in various research fields, including urban spatial structure, regional spatial structure, behavior and the built environment, and urban governance, ushering in the "big data era" of planning research [6]. From the late 2010s to the present, artificial intelligence technology has also attracted significant attention in the planning discipline [7]. In particular, machine learning has gained attention from both domestic and international planning researchers, with related academic papers rapidly increasing after 2018 [8]. The wave of artificial intelligence in urban and rural planning is still gaining momentum [9]. Digital planning technologies have become widely used in planning research, with research topics spanning various directions.

In the current digital era, digital planning technologies have become mainstream in the planning field. Although there is a wide variety of digital planning technologies currently used in planning research and practice, there remain many unresolved questions regarding how to understand digital planning technologies themselves and the effects and changes brought about by their rapid development. This paper aims to address these issues by first defining the concept of digital planning technologies. It will then review the evolution of digital planning technologies from the perspectives of data and knowledge, systematically organizing their technological paradigms. Finally, it will discuss the research frontiers and challenges of digital planning technologies and look ahead to the future trends in digital planning technologies within urban and rural planning.

1. Scope and Uses of Digital Planning Technologies

1.1 Distinction Between Digital Technologies and Digital Planning Technologies

To accurately define the concept of digital planning technologies, it is necessary to begin by understanding the meaning of the word "technology." The definitions of "technology" in different dictionaries are generally consistent and are explained in terms of the relationship between science and technology, stating that "technology is the application of specific methods derived from science in practice" [1]. From the relationship between technology and science, it becomes clear that the technologies used in current urban and rural planning research and practice can be classified into two categories.

The first category can be directly referred to as "digital technologies." Although technologies such as virtual reality, cloud computing, and the Internet of Things (IoT) have been applied in the planning industry, the science driving these technologies is computer science. The specific application of these technologies in planning relies on scientific methods and is not significantly different from their application in other fields or disciplines. A typical example is the use of virtual reality technology in planning outcomes presentations and database technology in planning information management.

The second category can be referred to as "digital planning technologies." Digital planning technologies are methods that use digital technologies in various stages of urban and rural planning research and practice. These technologies are used to analyze the current state of planning, model predictions, formulate proposals, select plans, implement planning, and monitor and evaluate planning outcomes. Although these technologies are based on digital technologies, they are driven by knowledge from the planning discipline, rather than computer science. In specific terms, the application of these technologies in the stages of current situation analysis, modeling, proposal formulation, plan selection, implementation, and evaluation of planning outcomes relies on scientific methods that differ significantly from applications in other fields.

Before the advent of digital technologies, various planning technologies already existed. One example can help illustrate the relationship and differences between "digital technologies" and "digital planning technologies." In the early 1960s, McHarg proposed the use of overlay techniques for land suitability analysis. He used hand-rendered transparent films and manually overlapped light sheets to implement the "layered" method. The "layered" method created by McHarg is a planning technique driven by the "design with nature" planning philosophy proposed by McHarg, which is a knowledge of the planning discipline [10]. McHarg's planning technology inspired early GIS researchers in the 1960s and led to the development of GIS spatial overlay functions, which later became one of the core spatial analysis functions of GIS. GIS spatial overlay is a "digital technology," driven by the science of geographic information science. After the 1980s, land suitability analysis based entirely on GIS overlays was developed [11-12], becoming a "digital planning technology." The knowledge driving the GIS-based land suitability analysis technique is still rooted in the planning philosophy that McHarg proposed. This example clearly shows the need to distinguish between "digital technologies" and "digital planning technologies."

1.2 Types of Uses of Digital Planning Technologies

After distinguishing digital technologies and digital planning technologies, we can discuss the different uses of digital planning technologies. Digital planning technologies can be categorized into three types based on their uses: analysis of planning effects, simulation of planning phenomena, and decision-making for planning objects. Analytical uses refer to the analysis of effects, factors, and mechanisms. The term "diagnosis" commonly used in recent years is a typical analytical use. For example, analyzing public perceptions of communities through spatiotemporal big data can effectively diagnose the effectiveness of community governance [13]. Simulation uses include modeling and simulation, with the term "scenario simulation" being a typical example. For instance, simulating the impacts of implementing compact city policies on public services and urban finances [14]. Decision-making uses refer to the formulation and selection of planning proposals, which are core to planning. For example, using deep neural networks to generate the optimal street network plan [15]. All three uses of digital planning technologies rely on various digital technologies as basic tools, but they are driven by the knowledge from the planning discipline in the stages of current situation analysis, modeling, proposal formulation, plan selection, implementation, and evaluation.

2. Urban Modeling Technology: Knowledge-Driven and Data-Driven

2.1 Urban Modeling Technology Since the 21st Century

Urban modeling technology is a historically significant planning technology. Emerging in the 1950s, urban modeling was initially not a digital planning technology, as models required manual calculations. During the 1960s, urban modeling technology became widely accepted, driven by the rational planning ideology, which promoted the development of urban models, particularly large-scale urban models. Decision-making was the primary use of urban modeling technology, which is referred to in planning history as the era of rational planning. The rational planning movement ended in the 1970s, leading to widespread questioning and criticism of large-scale urban models [16]; however, urban modeling technology did not disappear and has continued to exist in academia [17]. Since the 1990s, urban modeling has integrated with digital technologies like GIS [18], making it a typical form of digital planning technology.

Since the 21st century, three types of urban modeling technologies have developed in parallel. The first type is the traditional large-scale urban models, which continue to evolve in the 21st century. The second type is the rule-based models that emerged in the mid-1990s, primarily fostered by GIS technology. The third type consists of micro-simulation models such as cellular automata (CA). These three types of urban models have continuously evolved in their technical paradigms and uses.

2.2 Knowledge-Driven and Data-Driven Urban Modeling Technologies

The first type of large-scale urban models is still used in land and transportation planning in metropolitan areas, with Urbanism being a typical example [19-20]. After the 1990s, large-scale urban models shifted from traditional decision-making uses to simulation uses, aimed at modeling the various impacts of future planning policies. In terms of technical paradigms, large-scale urban models are knowledge-driven planning technologies, where the principles of the models are built on planning knowledge, considering the interactions between space and transportation, as well as the decision-making principles of households, businesses, and governments. Large-scale urban models are often referred to as "black box knowledge" or "gray box knowledge" driven. This is because expressing the interactions of land, transportation, and environment requires complex mathematical formulas that encompass numerous parameters and are difficult to understand, making it hard to clearly and directly correspond to spatial planning goals and strategies.

The second type, rule-based models, is typified by CUF [21] and "what if" [22-23]. Rule-based models were initially developed to simulate policies, assess the potential impacts of planning policies, and evaluate the rationality and feasibility of planning strategies, rather than for decision-making. In terms of technical paradigms, rule-based models are still classified as knowledge-driven planning technologies, but their principles are expressed as clear and simple rules. For example, the CUF model first predicts total demand; then, it allocates land use based on land suitability [24]. These models are no longer based on mathematical formulas that involve spatial interactions or discrete choices. In contrast, rule-based models are known as “white box knowledge” driven, as they are based on explicit knowledge that formulates simple model rules. The emergence of such clear rule-based models is closely linked to the integration of digital technologies and GIS.

Tab.1 Technological paradigm and usage of urban modeling technology

X	Large-scale Urban Models	Rule-based Models	Microscopic Simulation Models
Technical Paradigm	Knowledge-driven	Knowledge-driven	Data-driven
Purpose	From decision-making to simulation	Simulation	Simulation

The third type of micro-simulation models includes the CA (Cellular Automaton) model [25] and the ABM (Agent-Based Model) [26]. These micro-simulation models were originally developed to predict and simulate future land use patterns, and they continue to serve this purpose. These models introduced CA and ABM from computer science, leading to the emergence of a new data-driven technological paradigm. Micro-simulation models rely on long time-series historical data to calibrate model transformation rules, requiring the use of long-term historical data to train the model in order to predict future land use changes. For example, using 200 years of historical data to calibrate the model and simulate land use evolution over the next 50 years [27]. CA, originating from computer science, introduced data-driven modeling methods. The core of the cellular automaton model is its transformation rules, which do not incorporate planning theories or principles. The rules are "trained" from data. This "trained" knowledge, even if it exists, is considered "black-box knowledge."

From the perspective of data-driven and knowledge-driven technological paradigms, knowledge has always been a key term in urban modeling technologies. Traditional large-scale urban models are based on "gray-box knowledge"②, rule-based model foundations are based on "white-box knowledge," and micro-simulation models introduced a "data-driven" modeling paradigm, bringing about "black-box knowledge" (Table 1). Currently, urban modeling technology is more commonly used as a laboratory for simulating urban spatial evolution, with simulation being the mainstream application, rather than the decision-making tool of the rational planning era. Whether knowledge-driven or data-driven, urban modeling technologies today are primarily used for simulation and cannot effectively meet the needs of decision-making.

3. Data-driven Spatio-temporal Big Data Planning Technology

3.1 Evolution of Spatio-temporal Big Data Technology

Spatio-temporal big data has been part of planning disciplines for more than 10 years. Spatio-temporal big data itself can serve as a digital technology in planning. The earliest Mobile Landscapes project, which sensed urban activity intensity and spatio-temporal changes through mobile phone call volumes, utilized spatio-temporal big data, which was still considered within the realm of digital technology [28]. Over the past decade, spatio-temporal big data in urban and rural planning has gradually evolved from a digital technology into a digital planning technology for studying the relationship between urban space and urban activities. It has become an effective supporting planning technology in research on urban spatial structure, regional spatial structure, behavior and the built environment, urban governance, and other planning topics. Spatio-temporal big data planning technology supports the research of "urban activities" and "urban space" from four aspects: "perceiving spatio-temporal phenomena of activities in space, recognizing spatio-temporal patterns of activities in space, discovering spatial factors affecting activities, and exploring the mechanism of interaction between space and activities" [6]. These four aspects of spatio-temporal big data planning technology should be understood within the data-driven and knowledge-driven technological paradigms.

3.2 Data-driven Research on Activities and Space

"Perceiving spatio-temporal phenomena of activities in space" refers to the use of spatio-temporal big data to quantify and describe the spatio-temporal phenomena of activities in urban spaces, without involving the underlying influencing factors or mechanisms. In this technical type, spatio-temporal big data serves as a technology for perceiving the spatio-temporal characteristics of urban activities. For example, the Mobile Landscapes project used mobile phone call data to measure the spatio-temporal variation of urban activity intensity [28]. "Recognizing spatio-temporal patterns of activities in space" refers to using spatio-temporal big data to summarize spatio-temporal patterns and regularities of urban activities. For instance, using spatio-temporal big data to derive the travel patterns of differentiated populations [29]. This type of research either starts from time or space to explore activity patterns and regularities but does not consider the interaction mechanisms between space and activities. Both of these types of spatio-temporal big data research are data-driven.

"Discovering spatial factors affecting activities" refers to using spatio-temporal big data to identify the spatial factors behind urban activities. For example, using multi-source spatio-temporal big data to infer urban functions from the spatio-temporal characteristics of urban activities [30]. This is a technique for interpreting urban function information from the data. "Exploring the mechanism of interaction between space and activities" refers to using spatio-temporal big data to explore the characteristics of the interaction between urban space and urban activities and to understand their mechanisms. For example, using spatio-temporal big data to measure the spatial service range of different functional urban commercial centers and verify the central place theory in commercial center system planning [31]. This is a technique for interpreting information from the data on urban activities and urban space to verify existing disciplinary knowledge. These two types of spatio-temporal big data technologies are also data-driven.

Thus, spatio-temporal big data planning technology is always a data-driven paradigm, extracting information from data and discovering new phenomena or verifying existing knowledge. From its inception, spatio-temporal big data planning technology has always been used for analysis, effectively solving spatial and activity analysis, but it is still not capable of simulating or supporting decision-making (Table 2). Spatio-temporal big data is transitioning from "diagnosing" urban space to "predicting" urban space, and thus supporting planning decisions, which is one of the frontiers of spatio-temporal big data planning technology.

Tab.2 Technological paradigm and usage of spatial-temporal big data planning technology

	Spatial-temporal Phenomena of Activity in Perceptual Space	Spatial-temporal Laws of Activity in Cognitive Space	Discovering Spatial Factors Affecting Activity	Exploring the Mechanism of Interaction between Space and Activity
Technical Paradigm	Data-driven	Data-driven	Data-driven	Data-driven
Purpose	Analysis (analyzing phenomena)	Analysis (mining knowledge)	Analysis (explaining phenomena)	Analysis (explaining phenomena)

4. Artificial Intelligence Planning Technology: Knowledge-driven and Data-driven

4.1 Knowledge-driven Expert System Technology

Artificial intelligence is a long-established digital technology. The first wave of artificial intelligence was expert systems (ES), also known as knowledge-based systems (KBS). Around 1980, various fields explored the application of expert systems, including urban planning. The earliest artificial intelligence planning technologies emerged in the 1980s, with publications [32], monographs [33], and several systems appearing, such as expert systems for zoning [34] and site selection [35]. As early as the late 1980s, Chinese planning scholars began exploring urban planning expert systems. Chen Bingzhao et al.'s paper on the expert system for planning and construction management, published in 1989, is considered the first AI paper in the field of urban planning in China, almost synchronous with international exploration.

An expert system is a technology for assisting decision-making in planning objectives. Its characteristic is that it extracts expert knowledge, builds a knowledge base, and expresses knowledge in clear, rule-based formats, which the machine uses for decision-making. Expert systems belong to the typical knowledge-driven technological paradigm, where the key is to express planning knowledge as clear "if-then" rules, forming "white-box knowledge" in the knowledge base. The system makes decisions based on these "if-then" rules.

However, expert system planning technology encountered many difficulties [37]. By the 1990s, the academic community agreed that two difficulties were hard to overcome [33,38]. The first difficulty was knowledge extraction—how to summarize planning knowledge in plain language. The difficulty of expressing and extracting planning knowledge is the biggest obstacle to developing urban planning expert systems, a challenge determined by the nature of planning knowledge itself. The second difficulty was knowledge representation—how to express planning knowledge in standardized "rules." In fact, much of urban planning knowledge cannot be expressed as "if-then" rules, and many judgments are vague and unclear. The difficulty of extracting and expressing planning knowledge in clear rules is the reason why AI exploration in urban planning slowed or stagnated after the 1990s.

4.2 Data-driven Machine Learning Technology

Since the 2010s, machine learning has developed, sparking another wave of artificial intelligence. By the late 2010s, machine learning entered urban planning and has become the mainstream artificial intelligence planning technology today [8]. Unlike expert systems, machine learning no longer requires knowledge extraction but learns from large amounts of experiential "data," allowing the machine to accumulate knowledge and use the learned knowledge to make judgments and solve problems. Machine learning avoids the issue of planning knowledge being vague and difficult to express. On the other hand, machine learning's key element is data—it is "trained" through data. Big data has solved the problem of data sources for machine learning, which explains why machine learning became prominent in the big data era. Machine learning planning technology belongs to the data-driven technological paradigm.

Using machine learning to evaluate street built environment quality from street view images is now a common application [39]. Built environment quality evaluation is a completely data-driven planning technology that enables intelligent judgment through training with image big data.

Machine learning methods are also being explored for planning proposal generation [40-41]. For example, by learning the texture of urban road networks, it has become possible to automatically generate planning road networks that integrate with historical street patterns, a decision-making application in design [15]. It is worth noting that the former is used for analysis, while the latter is used for decision-making.

In 2023, Artificial Intelligence Content Generation (AIGC) emerged. AIGC involves deep learning, natural language processing, and other machine learning techniques and can be seen as a form of practical machine learning application. Based on general large models, specialized planning models are trained and used for generating planning reports, drawings, and other outputs. These models, once trained to understand specific planning task requirements, can generate diverse content like planning texts and images. This is an exciting development in artificial intelligence planning technology.

4.3 Understanding Artificial Intelligence Planning Technology through the "Data and Knowledge" Dimension

From the perspective of "data and knowledge," artificial intelligence planning technology has always been focused on knowledge. Early expert systems were "knowledge-driven" and based on "white-box knowledge," but acquiring planning knowledge was its biggest challenge. Today, machine learning planning technology allows machines to train knowledge models from data, resulting in "black-box knowledge." Even those who write algorithms cannot explain why the machine made a certain decision, as it is "trained" from data. Thus, even data-driven AI planning technology operates around knowledge, albeit in the form of "black-box knowledge."

In summary, artificial intelligence planning technology began with the knowledge-driven paradigm, while the development of machine learning brought about the data-driven paradigm. Whether knowledge-driven or data-driven, current AI planning technologies are mainly used for analysis and still struggle to meet decision-making needs (Table 3). The characteristics of the planning discipline itself determine that AI planning technology cannot rely solely on knowledge-driven approaches or data-driven ones, as machine learning leads to "black-box knowledge," and planning decisions cannot be based on "black-box knowledge."

Tab.3 Technological paradigm and usage of artificial intelligence planning technology

	Expert Systems (ES/KBS)	Machine Learning (ML)
Technical Paradigm	Knowledge-driven	Data-driven
Usage	Decision-making	Analysis, decision-making

Peng et al. [42] proposed a four-stage view from the perspective of the relationship between planners and AI, including Stage 1 AI-assisted, Stage 2 AI-augmented, Stage 3 AI-automated, and Stage 4 AI-automatized. The case mentioned earlier about automatically generating urban road networks belongs to Stage 3, where human planners set goals and AI provides solutions. The core idea of AI in urban planning in all four stages is that humans should not be excluded from the planning process, as planning always involves human-centered decision-making activities. Understanding artificial intelligence planning technology through the "data and knowledge" dimension helps better comprehend this core idea because human-centered decision-making activities require the support of "white-box knowledge" rather than "black-box knowledge" derived from machine learning.

5. "From Data to Knowledge": Prospects and Challenges of Digital Planning Technology

5.1 Knowledge-driven and Data-driven

The knowledge-driven technological paradigm relies on the knowledge of planning disciplines for analysis, simulation, and decision-making, and requires known planning knowledge as a foundation. For example, in large-scale urban models, planning knowledge is presented through mathematical formulas, and in expert systems, planning knowledge is presented in the form of rules. In the knowledge-driven technological paradigm, data is still essential, and it is applied based on disciplinary knowledge to fulfill analysis, simulation, and decision-making purposes.

The data-driven technological paradigm relies on data for analysis, simulation, and decision-making, and does not necessarily require pre-existing planning knowledge as a foundation. The data-driven technological paradigm either directly extracts the characteristics, influencing factors, and mechanisms of planning effects from the data, such as spatio-temporal big data planning technology, or trains models with data and uses them for planning analysis, simulation, and decision-making, such as machine learning planning technology.

Knowledge-driven originates from the knowledge system of planning disciplines and is an inherent technological paradigm of planning. Data-driven is an outcome of the integration of digital technology and planning technology. The integration of digital technology has greatly propelled the development of data-driven planning technology, solving many long-standing challenges in planning technology. Reviewing the evolution of three typical planning technologies since the 1990s, the data-driven technological paradigm has become the mainstream in contemporary digital planning technology.

5.2 Knowledge: White-box, Gray-box, Black-box

"Technology is the application of scientific methods in practice," which defines the relationship between knowledge and technology. Reviewing the evolution of the three typical digital planning technologies, they can be classified into "white-box knowledge," "gray-box knowledge," and "black-box knowledge." In rule-based models and expert systems, knowledge is white-box. In large-scale urban models, knowledge is gray-box. In cellular automaton planning technology and machine learning planning technology, knowledge is black-box (see Figure 1).

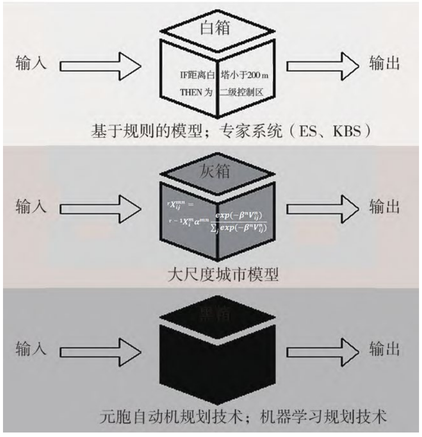

Figure 1: White-box knowledge, gray-box knowledge, and black-box knowledge of digital planning technology

"White-box knowledge" is reliable, and ideally, planning technology should be driven by "white-box knowledge." The biggest challenge faced by "white-box knowledge" in planning is knowledge extraction and knowledge representation—how to transform vague, implicit, and uncertain planning knowledge into rule-based "white-box knowledge." The journey of expert systems has shown that this difficulty is determined by the characteristics of planning knowledge itself, resulting in bottlenecks for knowledge-driven technological paradigms.

Data-driven planning technology bypasses the challenges of knowledge extraction and knowledge representation but brings about "black-box knowledge." Machine learning-based artificial intelligence planning technology is a typical example. While machine learning-based artificial intelligence planning technology produces impressive results, it has also been criticized for its "black-box knowledge" compared to the "gray-box knowledge" of large-scale urban models. Planning decisions cannot be simply based on "black-box knowledge," especially for significant planning decisions. This is why data-driven technological paradigms can support analysis and simulation purposes but struggle to support decision-making purposes.

5.3 Key Challenges in "From Data to Knowledge" for Digital Planning Technology

Planning itself is a human-centered decision-making activity, which determines the changes in the analysis, simulation, and decision-making purposes that digital planning technology assumes, as well as the evolution of data-driven and knowledge-driven technological paradigms. Critiques of rational planning have already shown that knowledge-driven decision-making in traditional planning technology has significant limitations. The data-driven paradigm has enriched and enhanced planning technology but has also brought about the issue of "black-box knowledge." This makes data-driven planning technology more suitable for analysis and simulation purposes and challenging to meet decision-making purposes because planning decisions should not be simply based on "black-box knowledge."

Supporting decision-making in planning has always been the pursuit of planning technology. To effectively support decision-making purposes, the future of digital planning technology lies in the "data and knowledge-driven" technological paradigm. Existing technologies are already capable of producing "black-box knowledge." If we can solve the challenge of learning "white-box knowledge" from data or discover and understand "white-box knowledge" from the results of machine learning, then using "white-box knowledge" for planning analysis, simulation, and decision-making purposes should be a reliable and trustworthy approach. Based on the "data and knowledge-driven" paradigm, the key is to address the transition "from data to knowledge," or more precisely, "from data to 'white-box knowledge'." Learning "white-box knowledge" from data and using it to drive planning analysis, simulation, and decision-making is essential.

The trend of digital planning technology is moving towards the "data and knowledge-driven" technological paradigm. To address the transition "from data to knowledge," which means learning patterns from data and using those patterns to support analysis, simulation, and decision-making purposes. Currently, AIGC (Artificial Intelligence Content Generation) and large models have demonstrated their value and prospects. Overcoming the challenges of expressing fuzzy and uncertain planning knowledge by using general large models and incorporating explicit knowledge from planning disciplines into specialized planning models can further support decision-making. This approach may be a feasible path to solving the transition "from data to knowledge" and is worth exploring.

6. Conclusion and Outlook

This paper defines the concepts and purposes of digital planning technology and, starting from the perspective of data and knowledge, delineates the two technological paradigms of digital planning technology. It elaborates on the research frontier and challenges of digital planning technology, leading to the following four conclusions.

First, the concept of digital planning technology is defined, distinguishing it from digital technology. Digital planning technology is the application of digital technology in various stages of planning, including current state analysis, modeling and prediction, plan formulation, plan selection, plan implementation, and monitoring and evaluation. It serves three purposes: analysis, simulation, and decision-making.

Second, digital planning technology can be categorized into two technological paradigms: data-driven and knowledge-driven. Knowledge-driven is inherent in planning technology, while data-driven is an outcome of the integration of digital technology. The data-driven and knowledge-driven technological paradigms determine the types of purposes in digital planning technology.

Third, current digital planning technologies used for decision-making purposes still need further breakthroughs. The data-driven technological paradigm can effectively support analysis and simulation purposes but is limited by its "black-box knowledge" when used for decision-making. The characteristics of planning disciplines themselves create bottlenecks for the knowledge-driven technological paradigm, such as knowledge extraction and representation. Both paradigms face challenges in better meeting decision-making purposes.

Fourth, the future trend of digital planning technology is to move towards the "data and knowledge-driven" technological paradigm. The key is to address the transition "from data to knowledge," which involves learning and extracting "white-box knowledge" from data, or discovering and understanding "white-box knowledge" from machine learning results, to drive planning analysis, simulation, and decision-making purposes. Digital planning technology should be understood as providing support for human-centered planning, as planning technology has always been used by humans and does not replace human decision-making—the characteristics of planning disciplines themselves determine this.

Note:

① This is a translation from the Cambridge Academic Content Dictionary (Cambridge University Press, 2017 edition) definition of technology: "Technology is a particular method by which science is used for practical purposes."

② In the critique of rational planning in the 1970s, large-scale urban models were directly criticized as "black boxes" of knowledge. If we compare large-scale urban models with knowledge in later models such as cellular automata and machine learning, large-scale urban models are more appropriately referred to as "gray boxes" of knowledge.

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