urban science

MDPI

Communication

Planning on the Verge of AI, or AI on the Verge of Planning

Thomas W. Sanchez

Urban Affairs and Planning, Virginia Tech, Arlington, VA 22203, USA; tom.sanchez@vt.edu

Abstract: The urban planning process is complex, involving social, economic, environmental, and political systems. Knowledge of how these systems interact is the domain of professional planners. Advances in artificial intelligence (AI) present planners with a ripe opportunity to critically assess their approaches and explore how new data collection, analysis, and methods can augment the understanding of places as they seek to anticipate futures with improved quality of life. AI can offer access to more and better information about travel patterns, energy consumption, land utilization, and environmental impacts, while also helping to better integrate these systems, which is what planners do. The adoption process will likely be gradual and involve significant time and resources. This article highlights several topics and issues that should be considered during this process. It is argued that planners will be well-served by approaching AI tools in a strategic manner that involves the topics discussed here.

Keywords: urban planning; artificial intelligence; expert systems

check for updates

Citation: Sanchez, T.W. Planning on the Verge of AI, or AI on the Verge of Planning. *Urban Sci.* **2023**, *7*, 70. https://doi.org/10.3390/urbansci7030070

Academic Editor: Tigran Haas

Received: 29 April 2023
Revised: 19 June 2023
Accepted: 26 June 2023
Published: 28 June 2023

1. Introduction

Research into artificial intelligence (AI) for urban planning began in the 1960s, influenced by the development of computer technologies with a broad range of scientific and industrial applications [1]. The development and implementation of planning applications, such as transportation and land use forecasting systems, however, were significantly limited by the lack of large-scale datasets and computing capabilities. Over time, academic and industrial research using advanced quantitative and spatial analyses commonly associated with AI has increased steadily; however, few of these have been adopted by the planning profession. While much of the current planning-related discussion concerning AI is related to "smart city" technologies that are being used to capture and analyze data for optimization processes, relatively less attention is being paid to urban planning and associated decision-making activities. Examples of this include scenario planning and generative designs. As global populations become increasingly urban, planning and management of these places are essential for sustainability, resilience, and equity in both the short and long term.

Just as urban planning gradually adopted computer technologies during the 1980s and GIS during the 1990s, the profession is now on the inevitable progression toward AI-augmented systems. The development and adoption of these technologies will likely need to be encouraged by universities where faculty are researching AI and where AI-related coursework will become integrated into planning curricula. Planning educators and professional organizations are on the verge of another wave of technological change. Yet, how will this current phase differ from the 1970s and 1980s when AI-related tools were being developed but were then not welcomed into planning practice? The primary differences today are changes in data availability, the pervasiveness of computer technology, and the general adoption of AI in many facets of daily life. The reluctance of the profession to accept technological change and the lack of appropriate education and training contributes to what Geertman referred to as the "implementation gap" [2] (p. 70).

This is an important time to assess current planning practices and how (or whether) they can benefit from emerging technologies such as artificial intelligence (AI). Methods

focused on pattern recognition (e.g., machine learning) are a particular area where urban planning can greatly benefit, especially with enormous quantities of urban data being collected and analyzed [3]. Procedures used by planners should be examined to identify opportunities for improvement and steps required for adoption. A challenge involved with this is eliciting expert knowledge, particularly for issues including quality of life, design, engineering, health, and law [4,5]. Planners are not the sole experts on urban processes and will also rely on technical expertise such as computer science and information technologies to generate solutions. An emphasis on technical expertise alone is insufficient in a planning context because planners also facilitate collective decision making and navigate political landscapes. Understanding the mix of urban expertise, politics, and power plays an important role in the further adoption of technology by the planning profession where expertise can support hierarchical structures that avoid transparency and inclusiveness [6]. Add to this the different types of planning expertise and experiential knowledge that are difficult to document and operationalize [7], and leveraging AI technologies within the planning profession becomes challenging.

This article begins by introducing AI and how it is entering the public sphere. It then goes on to briefly describe the complexity of urban planning and future cities, which can be seen as challenges for the adoption of AI tools. The role of expertise is then discussed as it relates to the planning process—particularly because expert systems have been tried in the past and may offer some useful insight into how we consider this next attempt at building intelligence into planning systems. Finally, the article highlights key challenges that land use planners will be confronted with as they move toward AI adoption. The objective is to call attention to some strategic matters that need to be considered along the way.

2. What Is AI?

AI can be defined as using computers to mimic or improve upon human intelligence, such as reasoning and experience-based learning. Although it has been used by computer scientists for some time, AI is now associated with a wide range of consumer goods and services that we use every day, from product design to marketing to customer feedback. To do this, many disciplines contribute to the process. AI employs methods from probability theory, economics, and algorithm design. In addition, computer science, mathematics, psychology, and linguistics are all used in AI development [8].

AI is also starting to impact governance and policymaking. Governments all over the world are utilizing AI technology to influence their responses to some of the most pressing problems of our time, such as the coronavirus pandemic [9], climate change [10], and the implementation of new data laws and governance structures [11]. At the same time, data laws concerning individual privacy are of significant concern prompting citizen privacy protection laws like the General Data Protection Regulation (GDPR) in the European Union (EU) [12]. Organizations at different levels of government are using AI-related tools to address the many challenges they face. Public sector organizations contribute to the delivery of services to citizens, such as healthcare and education and the creation of smarter and greener communities. However, challenges persist for the public sector in the face of a wave of new technologies (and their acronyms). Cities and counties are outlining their future information technology (including AI) initiatives through plans and strategies that highlight the costs and benefits of implementation (see, for example, [13–16]).

While AI refers to a very broad range of analytical methods, the primary elements involve a sequence of inputs, analysis, and outputs (Figure 1). An AI program takes inputs of a large quantity of data, analyzes it according to a set of rules, and produces outputs, which can take a variety of forms depending on the types of inputs and types of questions being addressed. What makes AI "intelligent" is its ability to use results from the analysis and outputs to update or improve the overall process: to learn. Planners might note that this logic is not unlike the basic process of planning practice—gathering information about an issue or a challenge, analyzing it to answer important questions, and producing plans or policies that improve the situation or address that challenge.

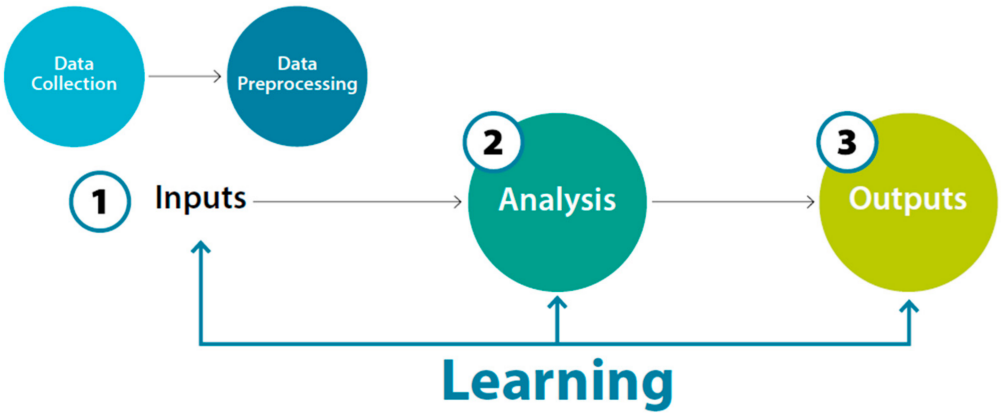

Figure 1. The basic analytical process for AI (source: Author).

Decades of AI research by computer scientists have focused on understanding the complexities of human thought processes and logic. The objective has been not only to understand how humans think but also to develop the means to improve upon it in a way that could be applied to nearly anything that involves intelligence and decision making [1]. AI is now associated with a wide range of consumer goods and services that we use every day, from product design to marketing to customer feedback.

Planning the cities of the future will require appropriate expertise and proper planning methods. There is general agreement that urbanization will continue to increase as a function of economic opportunity, while at the same time equity, environmental pressures, and infrastructure needs will continue to be major challenges. In addition, technology, connectedness, and digitalization are poised to accelerate at a rapid pace [17–20]. AI is expected to play an important role in future development activities as well as in the planning and management of cities for sustainability, resilience, and equity in both the short and long term. Planners must be prepared for the changes this means in how the cities of the future are planned, designed, and managed.

In addition to learning some of these AI-specific skills, planners will increasingly need to be conversant in other urban technology applications, such as those being used to create smart cities. Technology investments in infrastructure, the internet of things (IoT), and other technologies will transform how urban places function and therefore will be factored into how cities are planned and managed [21]. To stay relevant in a changing world, planners will need to know about these technologies and be prepared to engage with other disciplines involved in shaping the urban landscape, such as civil engineers, architects, landscape architects, and public administrators.

3. The Complexity of Urban Planning

The complex nature of human settlement has been long recognized. In discussing the future of cities, Harris [22] highlighted the fundamental challenges of urban planning that intermingle design, science, and policy—especially as they relate to understanding and optimizing urban systems. The mix of social, economic, environmental, and political aspects means that planning problems are sometimes considered wicked [23]. In addition, Wildavsky's [24] perspective on planning's expansiveness and perhaps overly ambitious reach are important to contemplate relative to planning's difficult-to-measure benefits [24]. It is useful to consider these pre-technological (i.e., pre-computerization) views of the complexity of urban planning (like those of Harris, Wildavsky, Rittel, Weber, and others) because they focus on the fundamental objectives and roles of planning and planners.

Dealing with a complex and diverse problem set requires solutions drawn from multiple domains that likely encompass various methodologies and sources of expertise. Given this caveat, one question is whether the urban planner is indeed the expert to be relied upon to understand how planning should occur [25]. Hendler [26] and Vigar [27] argued that planners possess a unique knowledge base and a definable set of expertise.

Others argue that planners' areas of expertise are represented by their skills as "network managers" to coordinate fragmented and assorted disciplines involved with managing the urban development process [28] (p. 245). Planning's venture into AI will require collaboration with domain experts, as did the moves into computerization (with computer scientists) and GIS (with geographers). The unique location of planning at the nexus of technical and political problems and the potentially fragmented nature of relevant expertise poses two major challenges to AI adoption in urban planning practice.

It is also important to consider what future cities will be like as we think about new approaches to planning these cities. The issues to be confronted will require appropriate expertise and proper planning methods. Well, we can only speculate about the condition and needs of cities in the next 30, 50, or 100 years, but there is general agreement that urbanization will continue to increase as a function of economic opportunity, while at the same time equity, environmental pressures, and infrastructure needs will continue to be major challenges. In addition, it is expected that technology, connectedness, and digitalization will continue to rapidly increase in importance [12,16–20]. AI is expected to play a role in future development activities as well as in the planning future.

4. Role of Expertise

Considering the multi-dimensional nature of urban planning, it is important to also ask, "What is 'to plan'? What do we need to plan for? Whose knowledge is necessary to plan?-which leads to "What do (professional) planners need to know?" [29] (p. 92). While these seem like large philosophical questions, they lay a necessary foundation for selecting planning tasks and operations that have the greatest potential for improvement through the application of AI technologies. Just as for any expert system, this requires an inventory of planning processes, knowledge, and expertise. Alexander [29] suggests that the kinds of knowledge needed for urban planning include (a) theory, (b) methods and skills, (c) judgment and good sense, (d) normative, and (e) substantive. It is easy to recognize from this mix of knowledge types that only some urban planning tasks fit into these categories. Hayes-Roth and Hayes-Roth [30] describe planning as the "predetermination of a course of action aimed at achieving some goals" (p. 275). While their definition is not specific to urban planning, it implies that designing processes (i.e., courses of action) and problem solving are principal aspects of planning.

The reality is that planning is not purely knowledge-driven but requires imagination in approaching challenging situations that have not been previously encountered and, therefore, involves significant uncertainty. In terms of connecting planning with AI, this highlights an issue stemming from the limited imagination of AI. For instance, machine learning (ML) relies on historical data, but the future may include innovations that fundamentally change problem spaces and cannot be predicted from even perfect knowledge of the past. Along with imagination, the element of common sense is another problem area for AI in planning, being a nearly boundless type of knowledge. As Mitchell notes, a prerequisite to trustworthy moral reasoning is generally common sense: what is harm, what are cause and effect, and counterfactuals [31]. Perhaps "common sense" is not the proper terminology in this case because it implies subjectivity that is strongly influenced by culture and socioeconomic status. Then again, perhaps it is appropriate because it suggests that an AI would need to have some awareness of cultural and socioeconomic factors to perform many of the tasks currently performed by urban planners.

From a knowledge acquisition perspective, common sense and tacit knowledge are closely aligned and are frequently difficult to capture and operationalize. Replicating or augmenting the network of urban planning tasks first requires the identification of relevant knowledge sources, both expert and non-expert, which assumes that needed information and experience can be explicated to create courses of action to solve urban planning problems. Along with the expert question is the need to incorporate stakeholder feedback. Because urban planning has a strong public orientation, stakeholders such as constituents or residents are commonly involved to provide feedback on objectives and

outcomes but rarely in a process that involves highly technical expert knowledge. In cases of "technocratic models of practice", the stakeholder cannot participate meaningfully and is effectively excluded [32] (p. 578). Sorting out the expert and stakeholder balance of power remains a challenge that planners must contend with, as there are and will be questions of transparency involved [33].

It is unlikely that the whole of planning will be replaced by AI-based rules and automation. So where will AI be most appropriate and how will the right planning tasks be selected? Batty [34] characterized "routine and nonroutine" (p. 1) aspects of planning to distinguish the variety of planning tasks in terms of frequency, scale, and intensity. This has implications for the selection of tasks, application of technologies, and anticipated benefits. Regularly executed tasks (routine planning) potentially generate more opportunities for knowledge accumulation, so long as adequate acquisition and evaluation mechanisms are in place. With repetition, experts develop "a skill of recognition, of 'seeing' old patterns in the new problem" [35] (p. 152). Therefore, developing an artificial expert represents a potential savings of time, effort, and cost. Under the current model, each generation of human planning experts needs to be trained and accumulate knowledge and experience over time. This is not to say that nonroutine functions cannot benefit from AI, but in general, they provide fewer learning opportunities and are operationalized with longer-term anticipated efficiency gains. The combination of task frequency and scale is also associated with increased data volume. This is important because machine learning methods tend to need substantial amounts of data before they can achieve acceptable levels of accuracy and reliability.

5. Expert Systems in Urban Planning

Expert systems in urban planning are computer applications that apply AI to narrowly defined tasks or functions [36]. As previously mentioned, the expected benefits of expert systems include efficiency gains through time savings and improved decision making. An enhanced understanding of tasks through the examination of procedural steps can help to codify expertise for transparency and knowledge management [37]. Significant attention was given to this form of AI during earlier periods of urban modeling and expert systems from the 1960s to the late 1980s. On one hand, the planner designs the modeling process based on an understanding of real-world dynamics, while drawing upon historical and cross-sectional data that explains interactions for predictive purposes. A missing element is the ongoing knowledge capture that provides dynamic sources of feedback to these planning processes, particularly as planners enter the profession and then retire, as alluded to previously. Academic research can be seen as playing a role but usually lacks the specificity of planning tasks, particularly related to experiential expertise. Sources of information about urban dynamics come from the past or represent current conditions and interrelationships as understood by experts. Both natural and artificial (i.e., urban) systems are complex, with interrelated actors and processes. However, modelers of urban systems cannot rely on the same long histories of scientific exploration that underpin their natural counterparts [38]. The application of these techniques to urban processes is still relatively new.

Identifying the parts or tasks of planning that can benefit most from AI involves understanding the intentions and knowledge of planners with direct experience. This process has been discussed in the context of expert systems, both inside and outside of planning. To identify planning tasks that are appropriately handled by expert systems, Waterman, Silverman, and Goodall [39–41] identified seven characteristics to guide the selection process. They suggest the following:

1. Genuine experts exist who can articulate their (problem-solving) methods;
2. Experts agree on solutions;
3. The task is not poorly understood;
4. The problem typically takes a few minutes to a few hours to solve;
5. No controversy over problem domain rules exists;

6. The problem is clearly specifiable and well bounded;
7. The problem solving should be judgmental, not numerical.

Han and Kim [42] argue that few urban planning tasks meet these criteria, particularly because of the complexity of urban places and human behavior mentioned earlier. In addition, referring to general decision making and cybernetics, Thomas [43] identified four criticisms that also challenged the appropriateness of expert systems for planning:

1. It is impossible to evaluate all the alternatives;
2. Goals are not always agreed upon and fixed in advance;
3. Real decision making was not like this;
4. Claims for objective neutrality were just excuses for methods without context that sidestepped political issues in planning (p. 383).

The first objection is not as relevant as compared to years ago because of improved AI technologies. For example, there is now little brute force on decision trees in AI chess programs or Go engines. Instead, they use Monte Carlo simulation and other methods to approximate probabilities of actions [44]. The same approach holds for urban planning actions. Goals and problem solving are often a question of optimization than arriving at a solution, especially because urban systems rarely reach equilibrium. However, references to real decision making and objectivity are perhaps less relevant in the context of more current technological applications. Along with the challenge of selecting tasks is also the definition and selection of planning problems to be addressed [45]. Prioritizing problems and tasks may likely be an iterative process as each task is better understood not only individually, but also relative to the planning process. To design expert systems or other AI applications, the process of knowledge acquisition or knowledge engineering is an essential first step [34,46,47]. This is where planning practice can benefit from collaborating with experts to understand these processes and seek to develop ontologies to inform the design of applications.

6. Connecting Research and Practice

Urban planning is no exception to the tension seen in many professions between theory and practice. Researchers are frequently more interested in characterizing problems, gathering information, and developing theories rather than finding actionable solutions [48]. Planning literature is rife with instances of how academic work either fails to influence day-to-day planning decisions or ignores political realities [49]. Planning academics are encouraged to conduct more action-oriented research, to ground their findings in real planning problems, to strive to understand what planners do, and to learn from practice to close this gap between research and practice-oriented problem solving [50,51]. At the same time, planning professionals are encouraged to use academic research as a source for new perspectives and approaches. The point is that academics and planning professionals should reevaluate the potential role that research can play—more specifically, the function of evidence and its place in planning practice. There is a sizable amount of research on AI applications and represents an opportunity for practice and research to connect.

7. Potential Impacts of AI on the Planning Process

Concerns have been expressed that separating planning tasks can result in specialties that inhibit "articulating a synthetic understanding of urban society" [52] (p. 211). This can force planners to take a reductionist view of urban development by performing analysis on specific questions that can more easily involve technological solutions such as computer modeling. These pieces then need to be reassembled as part of the overall plan-making process. On the one hand, it seems that a planner's focus on technical expertise can place them in a more objective position to advise decision making [53]. On the other hand, this assumes that planning tasks are modular and that each can be integrated to represent parts or the whole of urban systems. This is where the technical planner takes on a scientific role to reach a type of certainty while creating "computer simulation[s] of relations whose

consequences are imperfectly understood" [54] (p. 42). Should a planner be knowledgeable across these domains or are we asking too much?

However, the adoption of new methods and technologies is usually less disruptive than might be anticipated, because it is usually a gradual process that occurs incrementally. Consider geographic information systems (GIS), possibly the most significant technological advancement for planners of the past few decades. The use of GIS has progressed from the creation and updating of maps by specialized GIS technicians to the relatively sophisticated spatial analysis now available to anyone with access to a smartphone and GIS applications. This has taken place incrementally over many years and has positively transformed the practice of planning with minimal negative disruptive impacts. The adoption of AI by planners could follow a similar path.

AI is a set of many tools, and it is already integrated into many types of software, including word processing, email, spreadsheets, and GIS. While there will likely be new standalone AI applications or platforms developed for planners, most will be layered onto existing software or easy-to-access web-based platforms. However, like statistical methods used for making predictions, planners will need to know the underlying assumptions and be able to communicate the reliability of results. In some cases, new approaches to planning problems may be very different from those used in the past. These methods will involve new training and educational efforts.

8. Three Challenges to Implementation

Three challenges will impact how quickly, and efficiently urban planners will implement AI. Each of these will be briefly discussed to highlight how they play a role in the adoption of AI technology. These include (1) the need for new skills, (2) changing data needs, and (3) incorporating transparency.

8.1. The Need for New Skills

The digitalization of urban planning requires that planners learn new skills. However, AI is not the only driver of this change. Today's workplace is in a constant state of change with new technologies, changes in workplace culture, and evolving business practices. For many professions, the COVID-19 pandemic required the rapid adoption of video conferencing technologies and protocols to accommodate remote work, and electronic alternatives quickly replaced in-person contact. By necessity, we managed to learn new technologies quickly, some of which replaced long-standing previous practices. Updating skill sets to keep up with such changes is becoming a given.

The adoption of AI will differ among planners depending on their roles and responsibilities. It may include learning a new vocabulary of AI-related terminology, new software packages, programming languages, advanced statistical methods, and other AI-related concepts as discussed in this report. Upskilling to learn and maintain these skills will be an important element of adopting these new methods [55]. In addition to learning some of these AI-specific skills, planners will increasingly need to be conversant in other urban technology applications, such as those being used to create smart cities and "urban digital twins" [56]. Technology investments in infrastructure, the internet of things (IoT), and other technologies will transform how urban places function.

In addition, though most planners will not be directly involved with developing new AI applications, they may be engaging with technologists, such as computer scientists and application developers, to help them do so. As new urban technologies are being implemented, planners need to have seats at the table to represent the interests of community stakeholders as well as promote connections to better understand urban futures.

The readiness of planners to adapt and best use these new technologies is a crucial factor at this point. There are at least three factors involved in this: (1) the ability of AI now and in the future to have a significant impact on urban social and constructed environments, (2) the ability of AI now and in the future to meet planners' needs, and (3) the readiness and ability of planners to use AI technologies. The first of these is supported by research,

and the second will emerge as we see planners embracing new tools. Last, but not least, whether planners employ AI in their work will be greatly influenced by their existing degree of awareness and expertise in the field.

The successful implementation of these new methodologies will require new expertise in data analytic techniques and information systems, which has immediate implications for planning practice. Both internal and external elements, such as the knowledge and skill set of new employees (i.e., young planners), will play a role in the adoption process for planning organizations. Upskilling might take place through training exercises for experienced planners, perhaps led by newly hired employees who bring these abilities into an organization.

The adoption of new digital technology also entails investments in new computer equipment and systems, as well as human resources. It is important to evaluate the potential benefit, which will also depend on how many current procedures will be disrupted or altered.

8.2. Changing Data Needs

Urban planning has a tradition of being data-hungry for the many types of analysis that are used in the plan-making process [57], and data are critical for effective AI implementation. Three primary factors are data volume, quality, and management.

One of the biggest obstacles to AI implementation is the lack of sufficient high-quality data [58]. Complicated algorithms can require thousands or millions of observations. A model risks poor performance when additional data are added if it is initially trained on inadequate amounts of data. Planning often relies on information about people, households, and drivers, as well as their behaviors, which usually come from several sources. Planners must often combine federal, state, and local data. In some cases, the data will need to be anonymized, which is standard practice for data collected by the U.S. Census. This includes approaches such as "data swapping", which transfers data points from one observation to another, increasing security but potentially decreasing the value of the data for analysis to draw conclusions [59].

Potentially using more finely grained disaggregated data for AI models means running the risk of infringing on personal privacy rules that will constrain the availability of data. In the United States, the General Data Protection Regulation (GDPR), Payment Card Industry Data Security Standard (PCI DSS), Health Insurance Portability and Accountability Act (HIPAA), Federal Information Security Management Act of 2002 (FISMA), Family Educational Rights and Privacy Act (FERPA), and Gramm–Leach–Bliley Act are just a few of the laws that forbid the use of confidential or sensitive information (i.e., personally identifiable information, or PII) as input for machine-learning models [60]. While urban planners have not often used a credit card, healthcare, or educational data in the past, the increasing ubiquity of data collection and its commercialization will require ethical decisions about the appropriateness of certain data that may reveal personal identities.

Data quality and integrity can be a challenge as well. Any data that a machine-learning model reads will be used to inform its assumptions. If the data are inaccurate or incomplete, the rules produced will be fundamentally flawed. Training data must accurately reflect the population by including data sets that represent every demographic category. According to several studies, dark-skinned females are mistakenly identified by facial recognition 40 percent more frequently than white males [60]. Nonrepresentative training data sets are mostly to blame for this. Even if the data are inclusive of all demographic groups, it may still suffer from being incomplete or out of date [61].

Compounding this challenge is that many planners are not effectively trained in the basic elements of data management. Without effective IT management practices, planning organizations can find it difficult to answer basic questions, such as how many databases an organization has, which database contains a particular piece of information, or how data were originally collected. Within organizations, siloed functional groups and poor communication create challenges for sharing data resources with coworkers, particularly

for policymakers and administrators. Given that AI techniques rely heavily on data, these are serious issues. Organizations that lack the tools to understand and manage their data will find it more difficult to benefit from AI.

Public agencies struggle to deploy and manage AI systems because their staff lack fundamental data management skills [62]. Data governance and management practices should extend beyond IT departments to planning staff so they can better use and protect data assets. Though the learning curve for data administration is manageable, it is far more difficult to acquire the necessary abilities to create AI solutions. Planning organizations may need to prioritize the recruitment of planners with AI expertise.

8.3. Transparency and Explainability

Transparency in the public realm can be a challenge, and it has several facets. For AI, the main priority for planners should be being open about the use of AI for making predictions, recommendations, or decisions [63]. Transparency also involves enabling users to understand the elements of an AI system. The ability to deliver clear, relevant information regarding the outputs of an AI system and the justification for its use is another example of transparency, as is the facilitation of open, multistakeholder conversations and the creation of specialized organizations, where required, to promote public understanding and acceptance of AI systems.

Because AI and machine-learning models may be too technically challenging to be practical or helpful for understanding an output, transparency generally does not include disclosing source code or sharing proprietary datasets. Source code and datasets could also be considered intellectual property, which has specific legal protections.

Enabling those who will be affected by the output from an AI-based decision to understand how it was reached is referred to as explainability. This requires giving stakeholders simple-to-understand information that will allow those who are negatively impacted to contest outcomes, and, when possible, the causes and logic that led to those outcomes. For some AI systems, requiring explainability may harm accuracy, performance, privacy, and security, as it may necessitate condensing the solution variables to a set small enough for humans to understand, which may not be optimal in complex, high-dimensional problems. However, this will not likely be the case for many planning-related analyses.

The main factors in a decision; the data, logic, or algorithm behind the specific outcome; or an explanation of why similar-looking circumstances generated different outcomes may all be included when AI actors explain an outcome in clear and simple terms, as appropriate to the context. If applicable, personal data protection standards should be respected while allowing people to understand and contest the conclusion.

Related to transparency, AI can assist in identifying and minimizing the effects of human biases, but it also has the potential to exacerbate the issue by systematically introducing biases into sensitive application domains. Algorithms are susceptible to bias in several ways, even when sensitive factors like gender, ethnicity, or sexual orientation are accounted for [64]. Even large amounts of accumulated training data can be incomplete or inaccurate, reflecting previous poor decisions or biased analyses resulting from historical conditions.

We are all susceptible to and responsible for combating bias. Not only does bias harm those discriminated against, but it also harms everyone else by limiting people's participation in the economy and society. As a result of fostering distrust and delivering skewed results, bias lowers AI's potential for use in government, business, and society in general.

As complex as deep learning models can be, however, it should be noted that the human brain is the ultimate "black box". Humans can exaggerate or not even be aware of the reasons why they made a particular decision or selected a specific alternative. It may be nearly impossible to detect the source or type of bias in a human brain, while the logic and data used by computers can be carefully analyzed.

Solutions to combating bias involve expanding academic study regarding AI prejudice in urban planning and public policy and carefully considering the many ways that AI

may supplement our current methods of making decisions. We can improve AI decision making by using models that are meticulously constructed to avoid past biases. It is also important to immediately resolve any instances we witness of bias in AI. There may be no easy fixes in these cases, however. Defining and assessing "fairness" is exceedingly difficult. Researchers have devised technical definitions of fairness, such as mandating that models have similar outcome values across socioeconomic groups [65]. Different fairness criteria typically cannot be satisfied at the same time, which is a considerable challenge.

It is also necessary to determine when a system is deemed fair for use by deciding under what circumstances automated decision making can be permitted [66]. In some cases, human-in-the-loop algorithms or AI system responses, which include human intervention or review, will be needed to maintain control or oversight, especially in unusual circumstances that may not have significant machine intelligence to draw upon. These issues call for interdisciplinary approaches from planners, engineers, designers, ethicists, and social scientists. This can be especially tricky in the case of planning, where political forces play a role in decision making.

Some basic steps are recommended to address potential ethical concerns relating to bias. Planners should keep up to date on the ethical dimensions of rapidly evolving urban technologies, including AI, which is being continuously uncovered as more and more such applications are being implemented. In addition, planners and planning organizations can create accountable procedures that help reduce prejudice when they use AI, including the use of technical tools or operational techniques such as oversight committees or external evaluations.

9. Conclusions

AI is an emerging technology that is here to stay. As such, though planners and planning organizations will face challenges in adopting this new technology, the benefits of AI may be worth the risk. As AI becomes more commonly used and useful over time, the challenges of adoption will lessen, just as they have in other cases of innovation adoption. AI will play a significant role in the future operation and planning of cities. As more and more data are being generated all around us, urban planners will increasingly use AI to analyze and process this data to detect patterns, make predictions, and have a better understanding of urban dynamics. However, AI will not take over all aspects of planning, and neither will it replace planners. Rather, it will comprise a useful set of tools for a subset of planning tasks. The most suitable tasks for AI will be those that are repetitive, have quantifiable dimensions, and involve data that can be captured and maintained. While there may be concerns about the loss of entry-level positions that typically handle these tasks, shifting needs will be accommodated by changes in skills that young planners have already acquired.

Organizations such as the American Planning Association have acknowledged the accelerating pace of AI application development, particularly as it relates to the planning profession [8]. There are both substantial opportunities and challenges presented by these technologies, with more being revealed each day. AI can help planners in their work, enhance current planning procedures, increase efficiency, and allow planners to refocus their work on the human components of planning. The task at hand is to increase our knowledge and skills with appropriate AI methods to enhance planning practice in the service of creating more livable, resilient, and sustainable communities.

The promises and potential of AI are both intriguing and absorbing, but organizations must carefully prepare before investing resources in AI. It is important to prepare for change, and some interruption is to be expected. We are accustomed to our routines; therefore, getting staff to accept AI may be challenging. As described in this article, it is important to develop a thorough understanding of what AI offers an organization and be strategic in thinking through the potential challenges. Once an organization adopts AI, it is also important to track performance and evaluate the value and advantages of AI deployment to document a comprehensive understanding of how AI benefits the organization, staff,

and stakeholders. In addition, throughout the process of adopting AI, planners should be aware of the potential for ethical concerns related to its use as new types of data and analysis emerge for AI applications.

Finally, the future of AI holds transformative potential for urban planners, introducing tools that can significantly enhance decision making, optimize resource allocation, and improve overall livability. The integration of AI can lead to smart, responsive, and sustainable cities by predicting urban growth, analyzing traffic patterns, and assisting in planning sustainable infrastructure. Key considerations include the ethical use of data, maintaining privacy, and ensuring equitable access to the benefits of AI. As we move towards this AI-assisted future, it is crucial for urban planners to continuously engage in interdisciplinary dialogues, collaborate with AI experts, and involve the public to ensure that AI-based urban planning is transparent, accountable and, above all, serves the needs of all.

Funding: This research was partially supported by the National Science Foundation, Grant No. 2125259.

Acknowledgments: The author thanks the three reviewers for their very insightful comments and suggestions. He would also like to thank Trey Gordner and Theo Lim for their comments on previous versions of the article.

Conflicts of Interest: The author declares no conflict of interest.

References

1. Batty, M. The emergence and evolution of urban AI. *AI Soc.* **2022**, *38*, 1045–1048. [CrossRef]
2. Geertman, S. PSS: Beyond the implementation gap. *Transp. Res. Part A Policy Pract.* **2017**, *104*, 70–76. [CrossRef]
3. Sanchez, T.W.; Shumway, H.; Gordner, T.; Lim, T. The prospects of artificial intelligence in urban planning. *Int. J. Urban Sci.* **2022**, *27*, 179–194. [CrossRef]
4. Wang, M.; Zhou, T. Does smart city implementation improve the subjective quality of life? Evidence from China. *Technol. Soc.* **2023**, *72*, 102161. [CrossRef]
5. Han, Z.; Xia, T.; Xi, Y.; Li, Y. Healthy Cities, A comprehensive dataset for environmental determinants of health in England cities. *Sci. Data* **2023**, *10*, 165. [CrossRef]
6. Robin, E. The Politics of Urban Expertise. Ph.D. Thesis, University College London, London, UK, 2019.
7. Khakee, A.; Barbanente, A.; Borri, D. Expert and experiential knowledge in planning. *J. Oper. Res. Soc.* **2000**, *51*, 776–788. [CrossRef]
8. Sanchez, T.W. *Planning with Artificial Intelligence*, Planning Advisory Service Report 604; American Planning Association: Chicago, IL, USA, 2023.
9. Organisation for Economic Co-Operation and Development (OECD). Using Artificial Intelligence to Help Combat COVID-19. 2020. Available online: https://www.oecd.org/coronavirus/policy-responses/using-artificial-intelligence-to-help-combat-covid-19-ae4c5c21/ (accessed on 11 May 2023).
10. Dimock, W.C. What AI Can Do for Climate Change, and What Climate Change Can Do for AI. *Scientific American*, 5 April 2022. Available online: https://www.scientificamerican.com/article/what-ai-can-do-for-climate-change-and-what-climate-change-can-do-for-ai/ (accessed on 11 May 2023).
11. Rahnama, H.; Pentland, A. The New Rules of Data Privacy. Harvard Business Review. 2022. Available online: https://hbr.org/2022/02/the-new-rules-of-data-privacy (accessed on 24 December 2022).
12. European Commission. 2018 Reform of EU Data Protection Rules. 2018. Available online: https://commission.europa.eu/law/law-topic/data-protection/reform_en (accessed on 29 October 2022).
13. Barcelona City Council. Government Measures for Municipal Algorithms and Data Strategy for an Ethical Promotion of Artificial Intelligence. 2021. Available online: https://ajuntament.barcelona.cat/digital/sites/default/files/mesura_de_govern_intel_ligencia_artificial_eng.pdf (accessed on 1 November 2022).
14. The City of Los Angeles. SmartLA 2028: Technology for a Better Los Angeles. 2020. Available online: https://ita.lacity.org/smartla2028 (accessed on 15 October 2022).
15. Parikh, N.; Hohman, A. *NYC Artificial Intelligence Strategy*; The City of New York, Mayor's Office of the Chief Technology Officer: New York, NY, USA, 2021. Available online: https://nparikh.org/assets/pdf/nyc/nyc_ai_strategy.pdf (accessed on 13 February 2023).
16. County of Santa Clara, Technology Services and Solutions. FY22–24 Strategic Plan. 2021. Available online: https://it.sccgov.org/home (accessed on 11 May 2023).
17. Woetzel, J.; Rajadhyaksha, V.; Frem, J. Thriving Amid Turbulence: Imagining the Cities of the Future. McKinsey & Co. 2018. Available online: https://www.mckinsey.com/industries/public-and-social-sector/our-insights/thriving-amid-turbulence-imagining-the-cities-of-the-future (accessed on 2 October 2022).

18. National League of Cities. Future of Cities. 2022. Available online: https://www.nlc.org/initiative/future-of-cities/ (accessed on 5 October 2022).
19. Antunes, M.E.; Barroca, J.G.; de Oliveira, D.G. Urban Future with a Purpose: 12 Trends Shaping the Future of Cities by 2030. 2021. Available online: https://www2.deloitte.com/global/en/pages/public-sector/articles/urban-future-with-a-purpose.html (accessed on 11 October 2022).
20. U.N. Habitat. *World Cities Report 2022: Envisaging the Future of Cities*; United Nations Human Settlements Programme: Nairobi, Kenya, 2022. Available online: https://unhabitat.org/world-cities-report-2022-envisaging-the-future-of-cities (accessed on 2 October 2022).
21. Son, T.H.; Weedon, Z.; Yigitcanlar, T.; Sanchez, T.; Corchado, J.M.; Mehmood, R. Algorithmic urban planning for smart and sustainable development: Systematic review of the literature. *Sustain. Cities Soc.* **2023**, *94*, 104562. [CrossRef]
22. Harris, B. The city of the future: The problem of optimal design. In *Papers of the Regional Science Association*; Springer: Berlin/Heidelberg, Germany, 1976; Volume 19, pp. 184–195.
23. Rittel, H.W.; Webber, M.M. Dilemmas in a general theory of planning. *Policy Sci.* **1973**, *4*, 155–169. [CrossRef]
24. Wildavsky, A. If planning is everything, maybe it's nothing. *Policy Sci.* **1973**, *4*, 127–153. [CrossRef]
25. Pinson, D. Urban planning: An 'undisciplined discipline'? *Futures* **2004**, *36*, 503–513. [CrossRef]
26. Hendler, S. Do professional codes legitimate planners' values? In *Dilemmas of Planning Practice*; Thomas, H., Healey, P., Eds.; Aldershot: Avebury, UK, 1991.
27. Vigar, G. Planning and professionalism: Knowledge, judgment and expertise in English planning. *Plan. Theory* **2012**, *11*, 361–378. [CrossRef]
28. Sehested, K. Urban planners as network managers and metagovernors. *Plan. Theory Pract.* **2009**, *10*, 245–263. [CrossRef]
29. Alexander, E.R. What do planners need to know? Identifying needed competencies, methods, and skills. *J. Archit. Plan. Res.* **2005**, 91–106.
30. Hayes-Roth, B.; Hayes-Roth, F. A cognitive model of planning. *Cogn. Sci.* **1979**, *3*, 275–310. [CrossRef]
31. Mitchell, M. *Artificial Intelligence: A Guide for Thinking Humans*; Farrar, Straus and Giroux: New York, NY, USA, 2019; p. 127.
32. Goodspeed, R. Digital knowledge technologies in planning practice: From black boxes to media for collaborative inquiry. *Plan. Theory Pract.* **2016**, *17*, 577–600. [CrossRef]
33. Fischer, F. *Citizens, Experts and the Environment: The Politics of Local Knowledge*; Duke University Press: Durham, NC, USA, 2000.
34. Batty, M. Planning support systems and the new logic of computation. *Reg. Dev. Dialogue* **1995**, *16*, 1–17.
35. Olson, J.R.; Rueter, H.H. Extracting expertise from experts: Methods for knowledge acquisition. *Expert Syst.* **1987**, *4*, 152–168. [CrossRef]
36. Ortolano, L.; Perman, C.D. A planner's introduction to expert systems. *J. Am. Plan. Assoc.* **1987**, *53*, 98–103. [CrossRef]
37. Feigenbaum, E.; McCorduck, P.; Nii, H.P. *The Rise of the Expert Company*; Times Books: New York, NY, USA, 1988.
38. Dueker, K.J. Urban planning uses of computing. *Comput. Environ. Urban Syst.* **1982**, *7*, 59–64. [CrossRef]
39. Waterman, D.A. *A Guide to Expert Systems*; Addison-Wesley Longman Publishing Co., Inc.: Boston, MA, USA, 1985.
40. Silverman, B.G. Should a manager "hire" an expert system? In *Expert Systems for Business*; Boyd & Fraser Publishing Company: San Francisco, CA, USA, 1987; pp. 1–4.
41. Goodall, A. *Guide to Expert Systems*; Learned Information (Europe) Ltd.: London, UK, 1985.
42. Han, S.Y.; Kim, T.J. Can expert systems help with planning? *J. Am. Plan. Assoc.* **1989**, *55*, 296–308. [CrossRef]
43. Thomas, M.J. The procedural planning theory of A Faludi. *Plan. Outlook* **1979**, *22*, 72–77. [CrossRef]
44. Silver, D.; Hubert, T.; Schrittwieser, J.; Antonoglou, I.; Lai, M.; Guez, A.; Lanctot, M.; Sifre, L.; Kumaran, D.; Graepel, T.; et al. A general reinforcement learning algorithm that masters chess, shogi, and Go through self-play. *Science* **2018**, *362*, 1140–1144. [CrossRef] [PubMed]
45. Prerau, D.S. Knowledge acquisition in the development of a large expert system. *AI Mag.* **1987**, *8*, 43.
46. Hua, J. Study on knowledge acquisition techniques. In Proceedings of the 2008 Second International Symposium on Intelligent Information Technology Application, Shanghai, China, 20–22 December 2008; Volume 1, pp. 181–185.
47. Cooke, N.J. Varieties of knowledge elicitation techniques. *Int. J. Hum. Comput. Stud.* **1994**, *41*, 801–849. [CrossRef]
48. Baum, H.S. Teaching Practice. *J. Plan. Educ. Res.* **1997**, *17*, 21–29. [CrossRef]
49. Sager, T.; Ravlum, I.A. The political relevance of planners' analysis: The case of a parliamentary standing committee. *Plan. Theory* **2005**, *4*, 33–65. [CrossRef]
50. Forester, J. Reflections on the future understanding of planning practice. *Int. Plan. Stud.* **1999**, *4*, 175–193. [CrossRef]
51. Ozawa, C.P.; Seltzer, E.P. Taking our bearings: Mapping a relationship among planning practice, theory, and education. *J. Plan. Educ. Res.* **1999**, *18*, 257–266. [CrossRef]
52. Beauregard, R.A. Bringing the city back in. American Planning Association. *J. Am. Plan. Assoc.* **1990**, *56*, 210.
53. Checkoway, B. Paul Davidoff and advocacy planning in retrospect. *J. Am. Plan. Assoc.* **1994**, *60*, 139–143. [CrossRef]
54. Dyckman, J.W. The scientific world of the city planners. *Am. Behav. Sci.* **1963**, *6*, 40–44. [CrossRef]
55. Clint, A.; Cooke, K.; Gomez, A.; Hurtado, P.; Thomas, W.; Sanchez, S.S.; Wright, N. *AI in Planning Opportunities and Challenges and How to Prepare Conclusions and Recommendations from APA's "AI in Planning" Foresight Community*; American Planning Association: Chicago, IL, USA, 2022.

56. Ye, X.; Newman, G.; Lee, C.; Van Zandt, S.; Jourdan, D. Toward Urban Artificial Intelligence for Developing Justice-Oriented Smart Cities. *J. Plan. Educ. Res.* **2023**, *43*, 6–7. [CrossRef]
57. Boeing, G.; Batty, M.; Jiang, S.; Schweitzer, L. Urban analytics: History, trajectory, and critique. *arXiv* **2021**, arXiv:2105.07020. [CrossRef]
58. Roh, Y.; Heo, G.; Whang, S.E. A survey on data collection for machine learning: A big data-ai integration perspective. *IEEE Trans. Knowl. Data Eng.* **2019**, *33*, 1328–1347. [CrossRef]
59. U.S. Bureau of the Census. Comparing Differential Privacy with Older Disclosure Avoidance Methods. 2021. Available online: https://www.census.gov/content/dam/Census/library/factsheets/2021/comparing-differential-privacy-with-older-disclosure-avoidance-methods.pdf (accessed on 27 February 2023).
60. Moallem, A. (Ed.) *Human-Computer Interaction and Cybersecurity Handbook*; CRC Press: Boca Raton, FL, USA, 2018.
61. U.S. Government Accountability Office. *Facial Recognition Technology: Privacy and Accuracy Issues Related to Commercial Uses*; GAO-20–522; U.S. Government Accountability Office: Washington, DC, USA, 2020.
62. Sarker, M.N.I.; Wu, M.; Hossin, M.A. Smart Governance Through Big Data: Digital Transformation of Public Agencies. In Proceedings of the 2018 International Conference On Artificial Intelligence And Big Data (ICAIBD), Chengdu, China, 26–28 May 2018; pp. 62–70.
63. Gaur, L.; Sahoo, B.M. Introduction to Explainable AI and Intelligent Transportation. In *Explainable Artificial Intelligence for Intelligent Transportation Systems*; Springer: Cham, Switzerland, 2022. [CrossRef]
64. Roselli, D.; Matthews, J.; Talagala, N. Managing bias in AI. In Proceedings of the Companion 2019 World Wide Web Conference, Montreal, QC, Canada, 25–31 May 2019; pp. 539–544.
65. Corbett-Davies, S.; Goel, S. The measure and mismeasure of fairness: A critical review of fair machine learning. *arXiv* **2018**, arXiv:1808.00023.
66. Araujo, T.; Helberger, N.; Kruikemeier, S.; De Vreese, C.H. In AI we trust? Perceptions about automated decision-making by artificial intelligence. *AI Soc.* **2020**, *35*, 611–623. [CrossRef]