The Prospects of Artificial Intelligence in Urban Planning

Journal:	*International Journal of Urban Sciences*
Manuscript ID	RJUS-2022-0127
Manuscript Type:	Research Article (Original Paper)
Keywords:	Urban Planning, Technology, artificial intelligence, data science

The Prospects of Artificial Intelligence in Urban Planning

Abstract

Over the past several decades, urban planning has considered a variety of advanced analysis methods with greater and lesser degrees of adoption. Geographic Information Systems (GIS) is probably the most notable, with others such as database management systems (DBMS), decision support systems (DSS), planning support systems (PSS), and expert systems (ES), having mixed levels of recognition and acceptance (Kontokosta, 2018; Yigitcanlar et al., 2020). Advances in information technologies have moved very slowly in the field of urban planning, more recently concerning "smart city" technologies while revolutionizing other domains, such as consumer goods and services. Baidu, Amazon, Netflix, Google, and many others are using these technologies to gain insights into consumer behavior and characteristics and improve supply chains and logistics.

This is an opportune time for urban planners to consider the application of AI-related techniques given vast increases in data availability, increased processing speeds, and increased popularity and development of planning related applications. Research on these topics by urban planning scholars has increased over the past few years, but there is little evidence to suggest that the results are making it into the hands of professional planners (Batty, 2018, 2021). Others encourage planners to leverage the ubiquity of data and advances in computing to enhance redistributive justice in information resources and procedural justice in decision-making among marginalized communities (Goodspeed, 2015; Boeing et al, 2021). This article highlights findings from a recent literature review on AI in planning and discusses the results of a national survey of urban planners about their perspectives on AI adoption and concerns they have expressed about its broader use in the profession. Currently, the outlook is mixed, matching how urban planners initially viewed the early stages of computer adoption within the profession. And yet today, personal computers are essential to any job.

Introduction and Background

Urban planning researchers have been developing artificial intelligence (AI) methods dating back to the 1960s (Langendorf, 1985). AI at the time was a specialized and highly scientific endeavor, not typically conducted by professional planners. For a variety of reasons, AI did not take hold. But over the years, planning has considered a variety of other advanced methods with greater and lesser degrees of adoption and success. Geographic Information Systems (GIS) is probably the most notable, with others such as database management systems (DBMS), decision support systems (DSS), planning support systems (PSS), and expert systems (ES), having mixed levels of recognition and acceptance (Kontokosta, 2018; Yigitcanlar et al., 2020). The adoption of GIS, some will argue, has been primarily related to its cartographic capabilities and less to sophisticated spatial analysis techniques (Daniel and Petit, 2021). Part of the challenge is that some types of planning problems are appropriate for if-then, rule-based algorithms while others are based on more complex structures more in the vein of artificial neural networks. Advances in information technologies have moved slowly in the field of planning while revolutionizing other domains, such as financial services, healthcare, and consumer goods and services. Baidu, Amazon, Netflix, Google, and other companies have revolutionized AI to gain insights into consumer behavior and characteristics and improve supply chains and logistics. However, there has been much criticism that these organizations and others such as social media platforms, credit reporting agencies, and insurance companies engage in a modern version of the panopticon, observing, surveilling, and controlling people. Urban planning is a data-hungry activity that can capitalize on these technologies to gain new insights into and efficiencies for the communities they serve while at the same time maintaining particular attention to potential bias and negative social impacts.

Artificial intelligence (AI) is the theory and creation of computer systems that can carry out tasks that would typically need human intelligence developed largely within a paradigm of efficiency and neoliberal values. AI represents a variety of techniques including those used to understand and analyze imagery, natural language, quantitative data, and by detecting patterns and anomalous behaviors, with the ability to learn over time. Among other capabilities, AI provides tools for making inferences about what people want or will choose to do, which has direct implications for urban planning. Urban systems exhibit many predictable patterns that lend themselves to AI-related analyses, but there are substantial amounts of uncertainty leading to unpredictable outcomes. AI tools are themselves limited by the data (predictors and choice outcomes), and by modeling assumptions. It is essential to identify both how AI tools can ameliorate attentional limits and behavioral biases in urban planning, and also recognize how AI tools are susceptible to incorporating these factors into their design, resulting in similarly biased AI-based recommendations (see O'Neil, 2016 and Eubanks, 2018).

The combination of urban planning and data science applications can bring computational power to urban big data that can generate innumerable alternatives for decision-making processes. Human-AI interaction (e.g., "human in the loop") is often essential to combine these capabilities. However, when humans are excluded, fundamental "black box" problems can arise. AI techniques such as machine learning and deep learning are relatively opaque from the perspective of human users. On the other hand, with these rule-based and logic rules, AI algorithms supply useful results that could potentially make decision-making more transparent in some ways. But algorithms typically do not provide any justification or rationale for the results that are generated, so users of these algorithms are therefore faced with the decision of whether to accept the results at face value only, without the ability to question or understand the underlying process. Data gaps are also an issue. If the data being used to train the model does not represent the entire community, the outcomes and decisions will be biased. Transparency and traceability, while ensuring data privacy, are important for public decision-making and policy. New "Explainable AI" methods are needed to enable analysts to peer inside the algorithms and gain some understanding of how the analytical results were discovered by the algorithm, the process trail, analytical provenance, and data support (Adadi and Berrada, 2018)

This is an opportune time for planners to consider the application of AI-related methods given vast increases in data collection, increased processing speeds, and increased popularity and accessibility of AI methods. The potential of AI for planning, like that of other business and government sectors, was recognized in the late 1950s and early 1960s, but further advancement in adoption was limited by the lack of data about urban places and processes - an issue that is rapidly changing given the implementation of data collection sensors that track movement patterns, land-use changes, real estate transactions, energy usage, etc. (Thakuriah, Tilahun, and Zellner, 2017). A notable challenge is that planning problems are often “wicked” in nature compared to the “tame” problems that AI frequently addresses. For instance, medical diagnosis from X-rays is a “tame problem” addressed with voluminous supervised data classification compared to diagnosing urban blight with no straightforward criteria (Safransky, 2020). The more recent “digital twin” concept as a modeling approach that incorporates AI. Digital twins “digital replications of living as well as nonliving entities that enable data to be seamlessly transmitted between the physical and virtual worlds” using AI to make sense of output including monitored and modeled data takes this point even further as digitalization extends to three dimensions (El Saddik, 2018, p.87). Research on these topics by urban planning scholars has been increasing over the past few years, however, the evidence suggests that the results are gradually making it into the hands of professional planners (Batty, 2018). Some academics propose that planners shorten the time frames at which they plan to better overlap with such advances in cybernetics and urban operations research (Batty, 2021). Others contend that planners should use the ubiquity of data and advances in computing to enhance redistributive justice in information resources and procedural justice in decision-making among marginalized communities (Goodspeed, 2015; Boeing et al, 2021).

Along with the uptick in data availability, computing capabilities, and urban AI research, urban planning is poised to experience significant changes in technology applications for plan-making. The scholarly literature suggests there is an extensive range of prospective AI applications for planning, in domains as diverse as land use, zoning and permitting, environmental planning, and transportation. Many of these examples represent wicked problems within planning operations that among other things, do not have agreed upon rules, logic, or finite sets of possible outcomes. Many are used infrequently and perhaps do not represent significant improvements or cost savings compared to other more routine and regularly used methodologies. Therefore, as urban planners and planning organizations consider appropriate applications to improve their processes, it is wise to consider which parts of planning will benefit from the current stage of AI, and are not likely to cause unintended consequences. Significant advances still need to be made for AI to apply to the "wicked" problems of urban planning. This includes important elements such as who is involved in defining the problem, evaluation of AI tools, representativeness of data, and the time horizon involved. This can mean emphasizing the needs of planners first and the attributes of technology second, an approach that differs from what we currently observe where technology is developed through research processes with little consideration of current practice.

An important consideration at this stage is the willingness of planners to adopt and best leverage these new technologies. There are at least three parts to this, 1) current and future capabilities of AI to significantly influence the social and built environments of cities, 2) current and future capabilities of AI to meet the needs of planners, and 3) willingness and capacity of planners to adopt and leverage technology. We find evidence for the first of these in the literature (discussed later) and the second will develop over time as we observe planners adopt technologies. Finally, the current level of awareness and knowledge of planners about AI will significantly impact whether these technologies are used by the profession. Because these new methods will involve new skills and knowledge about data analytic methods and information systems to be successfully implemented, which has direct implications for planning practice. The adoption process involves attitudes and decisions internal to planning organizations as well as external factors, such as the skills that new hires (i.e., young planners) will bring to organizations. Such upskilling can occur through training activities for practicing planners or by new hires who have these skills and introduce them to an organization. These also involve investment in human resources and new computer technologies. The potential value will also involve the level of disruption or change in current practices and should be assessed. Technology diffusion processes can help to explain the process. There will be early adopters (usually in some kind of niche, such as academia), hybridization, and finally market growth (Geels, 2002).

Method

The objective of this article is to consider the questions above by drawing from the current literature as well as recent survey data collected from American Planning Association (APA) members. The literature provides a perspective from mostly researchers and scholars and the survey represents mostly professional planners. While the literature review and survey represent different perspectives, it can be argued that researchers are a likely source of application development that will lead to adoption by the planning profession over time. Our review of the literature provides an overview of scholarship pertinent to AI in urban planning. Through a comprehensive search, we identified and critically appraised publications on the topics of "urban planning," "planning support systems," "knowledge-based systems," "decision-support systems," "artificial intelligence," "machine learning", and "automation." Publications were targeted from disciplines allied with urban planning, however, some are on general topics of information technologies, information processing, big data, data analytics, and automation, and AI ethics due to the limited literature specifically on AI for urban planning practices. The goal is to document, critically evaluate, and summarize the scholarship identifying planning functions with potential artificial intelligence approaches.

Literature Review

The following review represents an initial exploration into how urban planners are using AI. For this, we searched for publications on the topic of AI applications to six major topics in planning: zoning, permitting, sustainability, transportation, water and waste, and urban design. While not comprehensive, these topics represent the breadth of planning functions that will likely be augmented or modified by AI techniques. We were also interested in the role of the domain expert (i.e., professional planners) and found that it varied considerably among the literature we reviewed. The continuum includes, 1) research that serves primarily as high-level technical research that applies advanced optimization techniques to planning problems, 2) research in which the authors at least tacitly state the study's benefits for planners, 3) research in which the authors demonstrate an understanding of planning workflows and tailor their inquiry and solutions based on that knowledge, 4) research that employs planning practitioners directly to validate methodologies, and 5) research in which the authors engage in iterative collaboration with planners.

The first set of studies is the least in tune with practitioners' needs and workflows. While the authors focus on topics that are in the same domain and theoretically relevant to planners, this research tends to be highly technical, highlighting the best ways to optimize planning-relevant processes like protected area zoning, energy consumption monitoring, and designing transportation networks. The literature provides little acknowledgment of how the innovative proposals would be implemented in typical planning departments (Li et al, 2011; Nosratabadi et al, 2019; Chui et al, 2018; Król, 2016). Li et al (2011), for example, propose a method for zoning protected natural areas using ant colony optimization, along with single-year coupling and merging-year coupling strategies to incorporate urban cellular automata. While this is a planning-relevant project, the authors make little mention of planning experts except to say that for the suitability analysis, "The weights for each variable should be decided according to expert experiences and domain knowledge" (Li et al, 2011 p. 585). Similarly, Chui et al's (2018) paper that proposes a "hybrid genetic algorithm support vector machine multiple kernel learning approach (GA-

SVM-MKL)" to carry out non-intrusive load monitoring (NILM) for 20 different kinds of electric appliances does not make any significant mention of practitioners who are involved in energy sustainability planning (p. 1). The authors note that "more attention needs to be devoted to the work in progress undertaken by key stakeholders involved in efforts geared toward optimizing electricity consumption" (Chui et al, 2018, p. 16). In general, this group of studies is so focused on identifying state-of-the-art techniques for planning applications that they fail to develop any discernible relationship with planners or delineate concrete ways to translate everyday planners' processes to technological solutions.

The second common type of research on artificial intelligence applications for urban planning are studies in which the authors take care to be slightly more aware of practitioners, and particularly aware of the need for the outcomes of their research to directly benefit practicing planners. Several articles on artificial intelligence in zoning exemplify this approach, as the authors note that their research attempts to reconcile the differences between the functional zones (i.e., how people use space) and the required or legal zones in a particular area (Shen et al, 2009; Soto & Frías-Martínez, 2011; Hao et al, 2020; Feng et al, 2018). With that said, many articles, in the urban zoning field and otherwise, primarily mention the benefits of their research to practitioners or what domain expert knowledge can add to their analysis, and they do so in the framing sections (e.g., introduction and conclusion), without much other explanation in the remainder of their study design and discussion (Shen et al, 2009; Soto & Frías-Martínez, 2011; Hao et al, 2020; Feng et al, 2018, Nikitas et al, 2020; Faghri & Hua, 1992; Sousa et al, 2014; Karami & Kashef, 2020; Lučić & Teodorovic, 2002).

A third and perhaps the most common role for planners in the reviewed literature includes articles in which the authors display a detailed understanding of practitioner needs and goals but do not directly collaborate with practicing experts for their inquiry. Their reasons for grappling with applied planning expertise and workflows more directly are diverse, but some do so based on local knowledge of their case study regions (Lin & Li, 2019; Mrówczyńska et al, 2019; Quan et al, 2019), or because their methods derive from expert-based systems (Yeh et al, 1986; Ülengin & Topcu, 2000).

A significant contingent of the articles reviewed was funded by regional or national government bodies with planning or planning-adjacent functions, like the Korean Ministry of Land, Infrastructure, and Transport, the Spanish Ministry of Economy, Industry, and Competitiveness, the Algarve Regional Coordination and Development Commission (Portugal), and government-owned Australian water utilities (Kim et al, 2020; Bienvenido-Huertas et al, 2020; Ortega-Fernández et al, 2020; Hadjimichael et al, 2016; Nguyen et al, 2018). In most cases, this funding mechanism creates a type of deliverable relationship between researchers and planners such that the researchers describe the needs and contributions of planners in more depth. For instance, Kim et al (2020) focus on how Korean planners are working to integrate BIM into their permitting process. With the stated goal of increasing the adoption of BIM-based permitting systems, they propose a prototype system, which includes modules for performing code checking, submission, pre-checking, and automated rule-making. In the modules, the authors aim to address common problems in the traditional permitting process with various automation tasks and unified document management (Kim et al, 2020). These researchers still do not collaborate directly with planners, but their research is much more closely aligned with practitioners' needs and considerations.

While research that focuses on pure technical innovation or only tacitly acknowledges planners are often funded by national sources, like different national scientific foundations, none of the articles we reviewed that fell into the categories of lower practitioner collaboration (see above) were funded by government organizations with urban planning functions.

The last two groups consist of a small number of researchers who directly collaborate with practicing planners for their studies. In the case of Shao et al (2015), the authors work with several stakeholders, including regional authorities, citizens, and conservation agencies, to help define an evaluation scheme (leaving room for changing weights based on different viewpoints in practice). They then implement a novel, “improved” version of the Artificial Bee Colony optimization algorithm for complex zoning in an area known for ecotourism. Zhang et al (2020) take a slightly different tack, engaging with ‘operators’ (who are outside experts, including planning practitioners and others) to test and validate their methodology after it has already been developed. In both of these articles, the relationship between practitioner and researcher is a transactional one, of “definition” or “validation” at either end of the research process, not an iterative process.

In Shahi et al (2019) and Messaoudi et al (2019), though, more back-and-forth collaboration between researcher and practitioner exists. In Shahi et al (2019), the authors first validated their methodology with a panel of practicing domain experts coordinated by the Residential Construction Council of Ontario (RESCON), the organization that largely funded the research project. The panel reviewed the proposed framework, provided feedback, and accepted a revised version as a “roadmap” for Ontario municipalities. In Messaoudi et al (2019), the authors directly interface with planners and other permitting practitioners by surveying those who work in municipal building departments. They regard this as the best way to find out about the current permitting processes across Florida, and it precedes any design and execution of new processes. In Messaoudi et al (2020), the authors use the framework that came out of the survey as their baseline and develops a proof-of-concept for virtual permitting that they then validate using practitioners’ expert knowledge about the permitting process from survey responses in a single case city, Gainesville, FL. Notably, even in these situations, where researchers worked collaboratively with planners, no articles explicitly mentioned the opportunity for practitioners to give feedback regarding mitigating bias or taking into account algorithmic transparency in the proposed artificial intelligence solutions. In that way, the collaboration between planners and researchers is still limited in scope.

As mentioned earlier, our literature review was oriented toward AI applications for practicing planners. The literature we reviewed was representative of other publications we also found in our search, most of which took a research approach to the development of applications, with little documented interaction with professional planners. This is not to say that there is no practical relevance to the examples provided, however, we expected that planners being the experts on the procedures involved, would play an explicit role in the conceptualization, design, and implementation of AI tools.

Survey Results

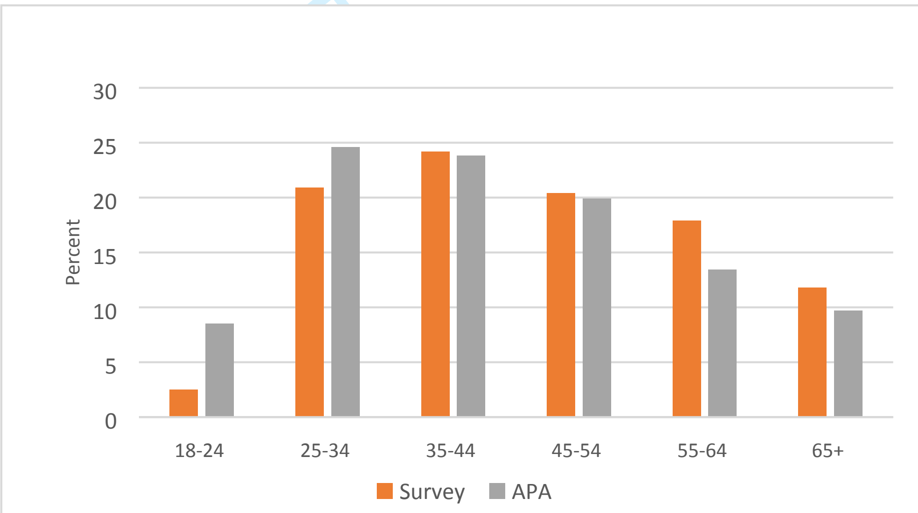
As mentioned previously, the objective of the survey was to assess the current understanding, experiences, and perspectives of urban planners about emerging information technologies, related to AI. The survey was interested in drawing from a broad range of planners, whether actively engaged in using these technologies or not. The survey was sent to 30,784 current members of the American Planning Association (APA) by email. Of those emails, just over one-third were opened (10,817), and 533 viewed the survey. A total of 397 complete survey responses were received. The survey consisted of ten questions about self-reported levels of knowledge about AI, perceived levels of appropriateness for several sub-areas of planning, the likelihood of adopting AI tools, and respondent demographic characteristics. Respondents were also asked about their definitions of AI to better understand the context of their responses and viewpoints. The following is a summary of key survey questions pertaining to the research questions previously discussed.

Demographic Characteristics

The typical respondent to the survey was approximately 46 years old with over 16 years of experience. Over 60% were male and 75% were white. This compares to overall APA membership characteristics of 52% male and 69% white. We expected that age would be associated with a higher likelihood of having positive attitudes and significant skills with information technologies. Nearly three-quarters of respondents held a graduate degree (68% held a master's degree, and 5% held a doctorate).

The remaining one-quarter held a bachelor's degree or below. Degree types were predominately in planning (60 percent), and also included public administration (10 percent), architecture or landscape architecture (7 percent), geography (5 percent), and business administration (3 percent). In addition, 65% of respondents worked for public planning agencies, followed by private planning organizations (24%), non-profit organizations (3%), and other types (5%).

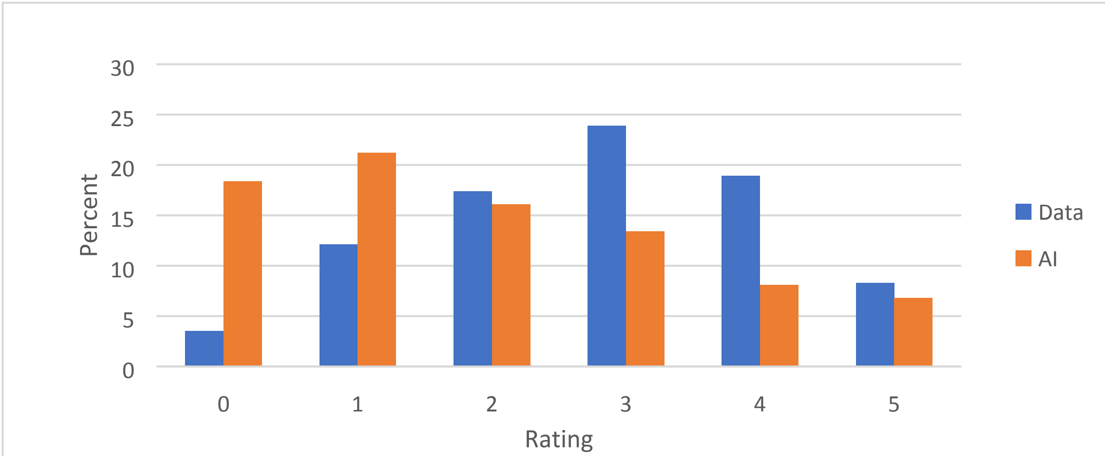
Figure 1. Age of Respondents Compared to APA Membership



Knowledge of Data Analytics and AI in Planning

The survey was interested in assessing respondents' level of knowledge and experience with data analytics and AI for urban planning. It was expected that survey respondents would be more familiar with standard data analysis techniques compared to AI for planning because general data analysis skills are commonly taught in planning schools and are frequently used in many planning analyses. The survey responses suggested that this was in fact the case. Self-reported levels of familiarity on a 0 to 5 scale bear this out with the mean rating of 2.3 for analytic methods in planning and 1.5 for AI in planning. Both of these are relatively low scores, which reflects limited analytical training, skills, or experience among the respondents in our sample.

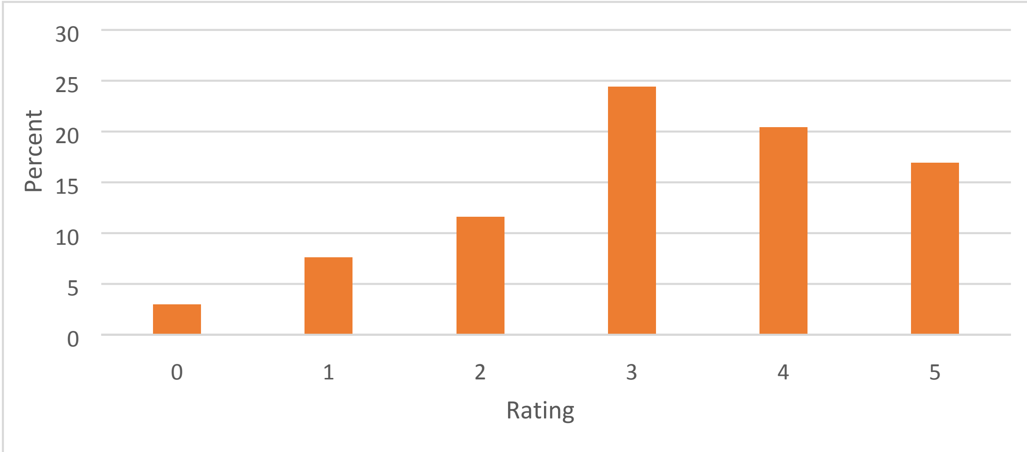
Figure 2. Levels of Self-Assessed Knowledge about Data Analysis and AI



Significance of AI in Planning and Suitable Application Areas

On the general topic of AI's significance to urban planning, survey respondents averaged 3.2 on a scale of 0 to 5 (where a score of 5 indicates “very significant”). Along with this, 48% of respondents identified applications they felt were suitable for AI in planning, while 43% of respondents identified application areas they felt were unsuitable. Whether there are suitable and unsuitable applications were asked in two separate questions, so the resulting groups were not mutually exclusive. For example, a respondent could state that community involvement was unsuitable for AI, but also state transportation analysis could be suitable. It is important to note that 43% of respondents did not know whether there were any suitable applications and 46% did not know if there were any unsuitable applications.

Figure 3. Respondent Rating for Significance of AI in the Field of Planning



Survey respondents mentioned transportation-related analysis and planning tasks as the top potential areas for AI applications (see Table 1). Transportation analysis tends to have more data available and more bounded planning questions compared to other types of planning issues. This is an example of a relatively tame problem given the inputs and potential outcomes from such analyses. The second most frequently mentioned area was plan review. This is a notable application because of its routine nature that is associated with rule-based processes. Like transportation, data analysis (including big data) and demographic analysis are well-suited to potential AI applications due to the quantitative nature of the questions being addressed. Other application areas like environmental, land use, and zoning have significant spatial dimensions that respondents considered appropriate for AI types of analysis as well.

Table 1. Top 10 Suitable Areas

Topic	***Frequency***
Transportation	87
Plan Review	30
Data Analysis/Big Data	26
Environment	21
Demographics	17
Land Use	16
Zoning	13
Economic	12
Community Involvement	11
Location Analysis	10

Table 2. Top 10 Unsuitable Areas

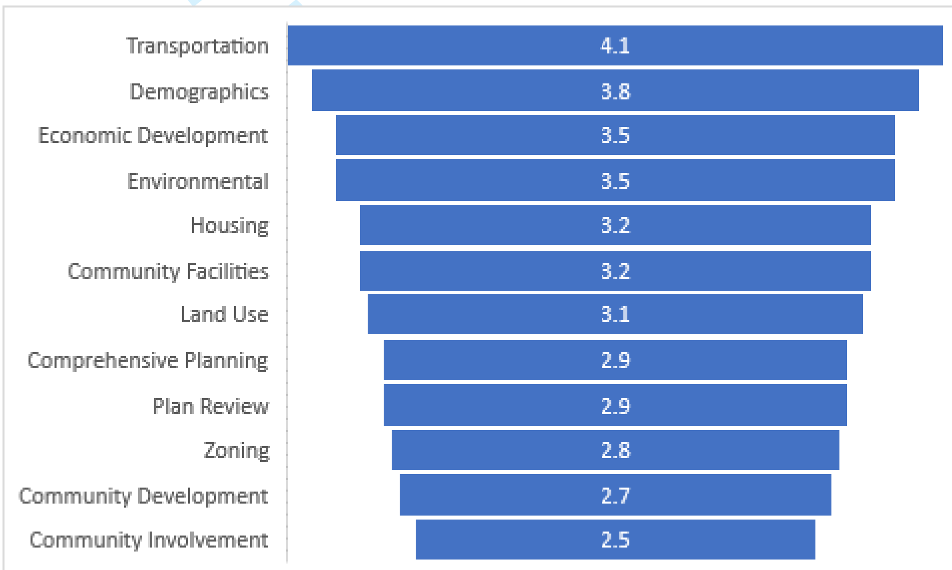
Topic	***Frequency***
Community Involvement	110
Comp Planning	13
Decision-making	12
All Areas	10
Zoning	8
Plan Review	7
Political	6
Data	5
Human/Social Interaction	5
Vulnerable Populations	4

In terms of unsuitable areas of AI applications, by far the most frequently cited area was community involvement, which was followed by comprehensive planning, decision-making, and "all areas" of planning (see Table 2). The two main themes of the areas seen as unsuitable by survey respondents are those with significant social dimensions and also those areas that involve complex processes such as comprehensive planning, decision-making in general, and political dimensions. These areas are likely to be considered wicked, based on the many social and political aspects involved. It is interesting to note that community involvement, zoning, plan review, and data analysis applications appear on both lists as being suitable and unsuitable. According to survey respondents, only about 7% of them (or their organizations) plan to adopt AI applications in the near future for their planning operations. The majority is split between not knowing if AI applications will be adopted and those who responded that they will not be adopting AI.

Rating of Planning Areas for AI

The survey also asked respondents to rate 12 particular planning areas in terms of their potential application to urban planning. The average respondent scores are shown in Figure 4. The results closely match those areas that respondents reported as being suitable and unsuitable for AI applications. This includes transportation and demographic analysis being rated the highest and community involvement and comprehensive planning being among the lowest (see Figure 4). This question was structured to also ask respondents if they are currently using AI in any of these or other areas. There were 33 responses that indicated that the respondent or their organizations were using AI (based on their understanding of AI). The most frequent area mentioned was transportation, with traffic counting and modeling being the primary applications. Others referred to data collection and quantitative analysis activities. There was a small number of mentions about chatbots, machine learning, and virtual reality as applications with potential as planning tools.

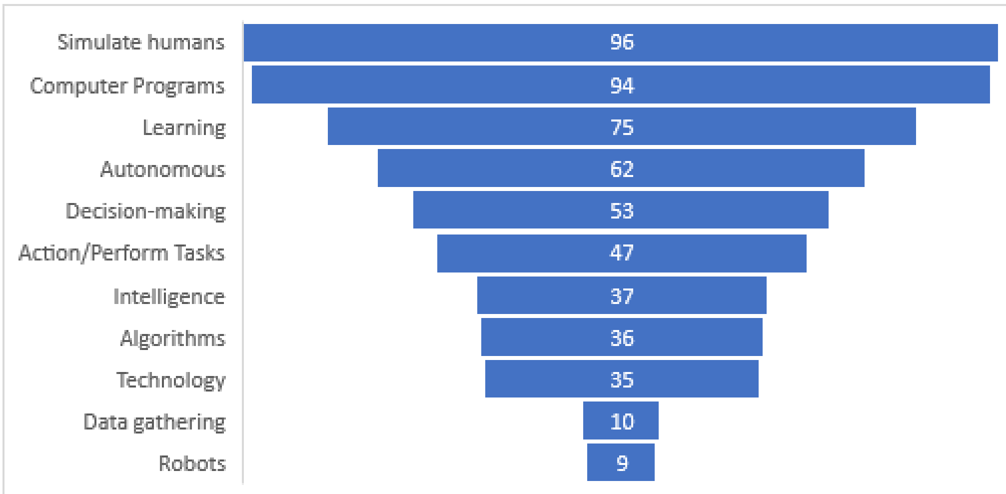
Figure 4. Rating of Potential Areas of Planning for AI (Scale of 0 to 5)



Planner Definitions of AI

Finally, we were interested in the ways that planners currently perceive AI. There were 315 definitions provided, within which there were 11 main themes (see Figure 5). Nearly one-third of the definitions referred to simulating or imitating human thought processes or actions. In most of these cases, the definition implied that AI would essentially automate what humans do, but with few mentions of increased accuracy or speed. Nearly one-third of the definitions also described AI in terms of being a computer program or system, while a smaller proportion referred to AI as a technology, which implies a more inclusive set of applications (including robotics which appears at the bottom of the list). Other frequently mentioned concepts included the ability of AI to learn over time, be autonomous, and perform decision-making or planning task completion.

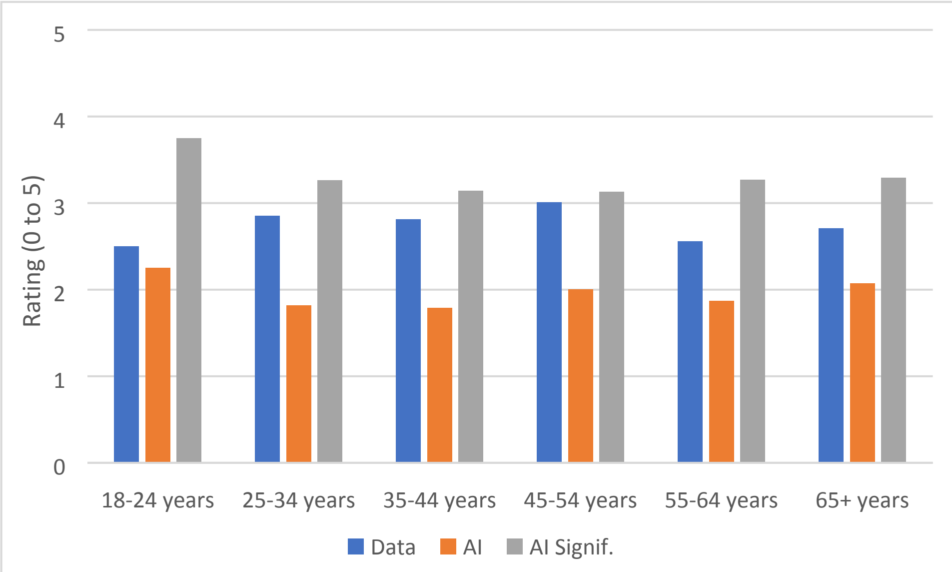
Figure 5. Respondent Definitions of AI (Topics)



Summary

This was the first survey of its type to collect data on the knowledge and uses of AI in urban planning in the U.S. The survey results are useful to understand not only the state of the practice but also the outlook for AI adoption by planning practitioners and others involved in planning. The survey results suggest that planners see transportation, demographic analysis, and other data-intensive planning tasks as being the most likely areas that AI can or will be utilized. At the same time, it should be noted that the level of knowledge about AI is low and the general outlook for AI adoption is currently moderate. But if general trends are any indication, opportunities for AI usage in urban planning will continue to proliferate as the technology advances. Earlier we alluded to the relationship between age, familiarity with technology, and views on AI. The survey results suggest that self-reported data analysis skills peak about mid-career, and familiarity with AI is relatively uniform across age groups. The results also suggest that the youngest age group (18-24 years old) rated the significance of AI to urban planning the highest compared to all of the other age groups.

Figure 6. Age, Self-Assessed Data Skills, AI Familiarity, and Outlook on AI Significance



Discussion/Conclusions

This article presents initial findings about the current state of AI in urban planning. We based our discussion on a literature review that drew from international researchers and scholars, who primarily reported on AI-related applications applied to planning in the areas of zoning, permitting, sustainability, transportation, water and waste, and urban design. Our interest was in areas that were most common to local land-use planning activities. Our review suggests that the types of current applications are relatively sophisticated and not likely suitable for planning practice, particularly for routine plan-making activities. In addition to our literature review, we also provided the results of the first ever national parentheses (U.S.) survey of planners about their experience, attitudes, and opinions about AI. Based on our knowledge of the planning profession, we expected that there would only be a small number of planners or planning organizations using AI, and there would be a tepid outlook on adopting these new technologies for planning operations. The assumption was correct about the low levels of current AI use by planners, which was also reflected in the responses about low knowledge levels about AI. At the same time, there were significant numbers of survey respondents who felt that AI will have a significant impact on planning practice in the future. This is an interesting finding given that respondents felt they did not know much about AI but at the same time, expected it to play an important role in future planning operations.

Researchers have an important role to play in adoption. If their work engages planners in the design and development of AI applications, it could improve planners' perceptions of AI usefulness and their capacity to use it. It could also inspire the private sector to offer AI products to the field and impress upon administrators the need to allocate more funding towards AI products. On the other hand, if researchers primarily produce technical papers that ignore planning practice, planners may view AI as a rarified technical topic without practical applications, choosing to remain in rational ignorance about its capabilities. So academic engagement with practitioners on the topic of AI could accelerate AI adoption in the field, while ignoring real-life needs may do the opposite.

Finally, in combining our findings from the literature review about AI and planning and our survey of professional planners, it is apparent that urban planning is in the early stages of innovation adoption. There is a substantial amount of research and innovation being discussed by researchers which appears in the academic literature, but it is not reflected in planning practice, at least in the US. This presents many future research opportunities in terms of how the planning profession will begin to incorporate AI-related technologies into practice. The research also leans heavily toward urban places where data is more easily collected and is readily available, unlike rural jurisdictions. A resulting urban-rural digital divide may develop over time as a result, negatively affecting planning activities outside of urban areas. In addition, this also represents a challenge to the profession and how these skills and knowledge will be obtained by current practitioners as well as planning educators in how they will prepare the next generation of planners equipped to bring innovation to planning organizations.

References

Adadi, A., & Berrada, M. (2018). Peeking inside the black-box: a survey on explainable artificial intelligence (XAI). *IEEE Access*, *6*, 52138-52160.

Batty, M. (2018). Artificial intelligence and smart cities. *Environment and Planning B: Urban Analytics and City Science*, 45(1), 3–6. https://doi.org/10.1177/2399808317751169

Batty, M. (2021). Planning education in the digital age. *Environment and Planning B: Urban Analytics and City Science*, 48(2), 207-211.

Bienvenido-Huertas, D., Farinha, F., Oliveira, M. J., Silva, E. M., & Lança, R. (2020). Comparison of artificial intelligence algorithms to estimate sustainability indicators. *Sustainable Cities and Society,* 63, 102430.

Boeing, G., Besbris, M., Schachter, A., & Kuk, J. (2020). Housing Search in the Age of Big Data: Smarter Cities or the Same Old Blind Spots? *Housing Policy Debate*, 1-15.

Chui, K. T., Lytras, M. D., & Visvizi, A. (2018). Energy sustainability in smart cities: Artificial intelligence, smart monitoring, and optimization of energy consumption. *Energies*, 11(11), 2869.

Daniel, C., & Pettit, C. (2021). Digital disruption and planning–use of data and digital technology by professional planners, and perceptions of change to planning work. *Australian Planner*, *57*(1), 50-64.

Eirinaki, M., Dhar, S., Mathur, S., Kaley, A., Patel, A., Joshi, A., & Shah, D. (2018). A building permit system for smart cities: A cloud-based framework. *Computers, Environment and Urban Systems,* 70, 175-188.

El Saddik, A. (2018). Digital twins: The convergence of multimedia technologies. *IEEE Multimedia*, *25*(2), 87-92.

Eubanks, V. (2018). *Automating inequality: How high-tech tools profile, police, and punish the poor*. St. Martin's Press.

Faghri, A., & Hua, J. (1992). Evaluation of artificial neural network applications in transportation engineering. *Transportation Research Record,* 1358, 71.

Feng, T., Truong, Q. T., Nguyen, D. T., Koh, J. Y., Yu, L. F., Binder, A., & Yeung, S. K. (2018). Urban zoning using higher-order Markov random fields on multi-view imagery data. In *Proceedings of the European Conference on Computer Vision (ECCV)* (pp. 614-630).

Geels, F. W. (2002). Technological transitions as evolutionary reconfiguration processes: a multi-level perspective and a case-study. *Research Policy*, *31*(8-9), 1257-1274.

Goodspeed, R. (2015). Smart cities: moving beyond urban cybernetics to tackle wicked problems. *Cambridge Journal of Regions, Economy and Society*, 8(1), 79-92.

Hadjimichael, A., Comas, J., & Corominas, L. (2016). Do machine learning methods used in data mining enhance the potential of decision support systems? A review for the urban water sector. *AI Communications*, 29(6), 747-756.

Hao, F., Zhang, J., Duan, Z., Zhao, L., Guo, L., & Park, D. S. (2020). Urban area function zoning based on user relationships in location-based social networks. *IEEE Access,* 8, 23487-23495.

Iliopoulou, C., & Kepaptsoglou, K. (2019). Combining ITS and optimization in public transportation planning: state of the art and future research paths. *European Transport Research Review, 11*(1), 1-16.

Karami, Z., & Kashef, R. (2020). Smart transportation planning: Data, models, and algorithms. *Transportation Engineering, 2*, 100013.

Kim, I., Choi, J., Teo, E. A. L., & Sun, H. (2020). Development of K-BIM e-Submission prototypical system for the openBIM-based building permit framework. *Journal of Civil Engineering and Management,* 26(8), 744-756.

Kontokosta, C. E. (2018). Urban Informatics in the Science and Practice of Planning. *Journal of Planning Education and Research*, 0739456X18793716. https://doi.org/10/gg2qhw

Król, A. (2016). The application of the artificial intelligence methods for planning of the development of the transportation network. *Transportation Research Procedia, 14*, 4532-4541.

Langendorf, R. (1985). Computers and Decision Making, *Journal of the American Planning Association*, 51(4), 422-433, DOI: 10.1080/01944368508976831

Li, X., Lao, C., Liu, X., & Chen, Y. (2011). Coupling urban cellular automata with ant colony optimization for zoning protected natural areas under a changing landscape. *International Journal of Geographical Information Science, 25(4),* 575-593.

Lin, J., & Li, X. (2019). Large-scale ecological red line planning in urban agglomerations using a semi-automatic intelligent zoning method. *Sustainable Cities and Society, 46*, 101410.

Lučić, P., & Teodorovic, D. (2002, November). Transportation modeling: an artificial life approach. In *14th IEEE International Conference on Tools with Artificial Intelligence,* 2002. (ICTAI 2002). Proceedings. (pp. 216-223). IEEE.

Messaoudi, M., Nawari, N. O., & Srinivasan, R. (2019). Virtual building permitting framework for the state of Florida: data collection and analysis. In *Computing in Civil Engineering 2019: Visualization, Information Modeling, and Simulation* (pp. 328-335). Reston, VA: American Society of Civil Engineers.

Mrówczyńska, M., Sztubecka, M., Skiba, M., Bazan-Krzywoszańska, A., & Bejga, P. (2019). The use of artificial intelligence as a tool supporting sustainable development local policy. *Sustainability,* 11(15), 4199.

Nguyen, K. A., Stewart, R. A., Zhang, H., Sahin, O., & Siriwardene, N. (2018). Re-engineering traditional urban water management practices with smart metering and informatics. *Environmental Modelling & Software*, 101, 256-267.

Nosratabadi, S., Mosavi, A., Keivani, R., Ardabili, S., & Aram, F. (2019, September). State of the art survey of deep learning and machine learning models for smart cities and urban sustainability. In *International Conference on Global Research and Education* (pp. 228-238). Springer, Cham.

O'Neil, C. (2016). *Weapons of math destruction: How big data increases inequality and threatens democracy*. Broadway Books.

Ortega-Fernández, A., Martín-Rojas, R., & García-Morales, V. J. (2020). Artificial intelligence in the urban environment: Smart cities as models for developing innovation and sustainability. *Sustainability*, 12(19), 7860.

Quan, S. J., Park, J., Economou, A., & Lee, S. (2019). Artificial intelligence-aided design: Smart design for sustainable city development. *Environment and Planning B: Urban Analytics and City Science,* 46(8), 1581-1599.

Safransky, S. (2020). Geographies of algorithmic violence: Redlining the smart city. *International Journal of Urban and Regional Research*, *44*(2), 200-218.

Shahi, K., McCabe, B. Y., & Shahi, A. (2019). Framework for automated model-based e-permitting system for municipal jurisdictions. *Journal of Management in Engineering,* 35(6), 04019025.

Shao J, Yang L, Peng L, Chi T, Wang X (2015) An Improved Artificial Bee Colony-Based Approach for Zoning Protected Ecological Areas. *PLoS ONE 10(9)*: e0137880. https://doi.org/10.1371/journal.pone.0137880

Shen, Z., Kawakami, M., & Kawamura, I. (2009). Geosimulation model using geographic automata for simulating land-use patterns in urban partitions. *Environment and planning B: planning and design, 36(5)*, 802-823.

Soto, V., & Frías-Martínez, E. (2011, June). Automated land use identification using cell-phone records. In *Proceedings of the 3rd ACM international workshop on MobiArch* (pp. 17-22).

Sousa, V., Matos, J. P., & Matias, N. (2014). Evaluation of artificial intelligence tool performance and uncertainty for predicting sewer structural condition. *Automation in Construction,* 44, 84-91.

Thakuriah, P. V., Tilahun, N. Y., & Zellner, M. (2017). Big data and urban informatics: innovations and challenges to urban planning and knowledge discovery. In *Seeing cities through big data* (pp. 11-45). Springer, Cham.

Ülengin, F., & Topcu, Y. I. (2000). Knowledge-based decision support systems techniques and their application in transportation planning systems. In *Knowledge-Based Systems* (pp. 1403-1429). Academic Press.

Yeh, C., Ritchie, S. G., & Schneider, J. B. (1986). Potential applications of knowledge-based expert systems in transportation planning and engineering. *Transportation Research Record, 1076,* 59-65.

Yigitcanlar, T., Desouza, K. C., Butler, L., & Roozkhosh, F. (2020). Contributions and risks of artificial intelligence (AI) in building smarter cities: Insights from a systematic review of the literature. *Energies*, 13(6), 1473.

Zhang, X., Du, S., & Zheng, Z. (2020). Heuristic sample learning for complex urban scenes: Application to urban functional-zone mapping with VHR images and POI data. *ISPRS Journal of Photogrammetry and Remote Sensing,* 161, 1-12.