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Artificial intelligence enabled participatory planning: a review

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ABSTRACT

Participatory planning is a democratic spatial decision-making process involving multiple stakeholders. The integration of artificial intelligence (AI) methods in participatory planning has the potential to improve the decision-making process. However, there are challenges and limitations that need to be addressed. In this paper, we systematically review the progress of AI-enabled participatory planning, identifying strengths and weaknesses. We used a Strengths, Weaknesses, Opportunities, and Threats (SWOT) framework for our analysis, highlighting the opportunities for advancing AI in participatory planning and the potential threats that may arise. Our study provides valuable insights into the current state of AI-enabled participatory planning, paving the way for future developments and improvements.

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Artificial intelligence; GIS; participatory planning; spatial decision support; AI challenges and limitations; democratic decision-making

Highlights

1. Deep learning elevates participatory spatial decisions.
2. AI's strengths in urban planning are on data, communication, and automation.
3. Emerging AI tools support richer urban research contexts.
4. Challenges remain on digital divide, trust, privacy, and accountability.
5. AI's potential is an ethical urban asset rather than a controversial adversary.

1. Introduction

As the need for equity in urban development is increasingly recognized, collaborative community-engaged processes (i.e. participatory planning) have been suggested as a better approach to local decision making than technocratic and authority-led models (Innes & Booher, 2018; Ye, Wu, Lemke, Valera, & Sackey, 2022). Arnstein (1969) created a typology of citizen involvement in local decision making and identified the lack of participatory approaches to urban planning. In her typology from low level participation to high level participation, non-participation meant that public decision-

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making lacked community consultation; tokenism meant the power holders would listen to the participants, but the participants did not have co-decision making power; and citizen power was the ideal with community members engaged in co-production of plans and making decisions. Improving participation in urban planning has been promoted by organizations such as International Association for Public Participation (*IAP2*, 2023). Organization for Economic Cooperation and Develoment (OECD, 2021) and the United Nations' in its sustainable development goals (United Nations, n.d.).

Participatory planning involves many activities, including identifying participants, determining roles and potential contributions of participants, identifying shared goals and the current local condition, communication between stakeholders, and the planning procedure. These activities are usually carried out in organized workshops involving reviewing documents, listening to domain experts, interacting with information systems, writing reports, and discussion and dissemination of results (Haqbeen, Sahab, Ito, & Rizzi, 2021; Martinez-Lopez et al., 2019; Ye, Du, & Ye, 2021). Increasingly, planning activities are aided by participatory mapping practices involving on-line tools and data-driven workflows underpinning the concept of 'smart cities' (Afzalan, Sanchez, & Evans-Cowley, 2017; Jankowski et al., 2021).

The practice of participatory planning has been evolving with new conceptual frameworks and technologies, including collaborative spatial decision support and Artificial Intelligence (AI) (Cai et al., 2018; Gorsevski et al., 2013; Jankowski & Nyerges, 2001; Jelokhani-Niaraki, 2021). AI is described as 'intelligence' demonstrated by machines that can perform like humans on tasks such as recognizing and localizing objects in images, summarizing an article, or recommending commodities to customers, tasks which would typically require human intelligence to solve but now can be largely automated with AI (An et al., 2023; Dwivedi et al., 2021; Sanchez, Shumway, Gordner, & Lim, 2022).

Though the concept of AI can be traced back to 1943 (Hochreiter & Schmidhuber, 1997; Wiggins & Ferreira, 1992), for example, machine learning is generally considered a subset of AI, referring to mathematical models that can learn patterns from data and infer unknown outcomes based on the new input, such as regression analysis. AI research and applications have been recently expanding into various domains largely due to the availability of big data and increased computing power (Allam & Dhunny, 2019; Li, 2018). It is then critical to explore how modern AI can support or even transform the current planning practice from a traditionally technocratic expert-driven process to a more inclusive participatory process increasingly relaying on data, computing capability, and large models. Hence, a systematic review of AI in participatory planning is timely given the advances in both fields.

The aim of this systematic literature review is to evaluate the current state of AI integration into participatory planning, a democratic spatial decision-making process involving multiple stakeholders. We seek to answer the following research questions:

(1) What are the key strengths and weaknesses of integrating AI into participatory planning processes as identified in the existing literature?
(2) What opportunities and threats can be observed for the future development and application of AI in participatory planning?
(3) How can these insights inform the advancement of AI-enabled participatory planning and mitigate potential risks associated with its implementation?

By addressing these research questions, our study aims to provide valuable insights into the current state of AI-enabled participatory planning, offering guidance for future developments and improvements in this interdisciplinary domain.

This paper is organized as follows: first, we outline the review methods used in this study. Then, we present our findings and discussions on the topic of AI-enabled participatory planning, using a Strengths, Weaknesses, Opportunities, and Threats (SWOT) framework to structure our analysis. In the findings section, we identify the benefits resulting from the integration of AI with participatory planning (i.e. strengths), as well as the limitations of the current state of integration (i.e. weaknesses). In the discussion section, we explore how new AI technology may further facilitate participatory planning processes (i.e. opportunities) and how the development of participatory planning can also advance the integration of AI. Finally, we consider possible negative aspects of such integration (i.e. threats).

2. Review methods

This paper investigates AI-enabled participatory planning in terms of the existing research, tasks, data, and methods. The review process at the most rudimentary level involves a four-stage analysis framework including literature search, screening process, selection of the screened literature, and adding referenced literature based on the screened results (Page et al., 2021). We limited our initial literature search to the SCI (Science Citation Index) and SSCI (Social Science Citation Index) databases to ensure the quality of the literature. Publications were retrieved from the databases using four groups of terms: (1) the paper must use AI technology; (2) the research needs to include multiple stakeholders; (3) the research question should be spatially defined; (4) the research topic must be related to participatory planning. While there has been a significant body of research focusing on spatial decision support systems (SDSS), relatively few research efforts have been dedicated to using SDSS in the collaborative planning context. In addition, only a few papers aimed at the level of participation between tokenism and citizen power based on Arnstein typology, while most papers focused on developing methods for delivering information to the public. We present the structured keywords lists and detailed review procedure in the appendix.

After conducting a thorough review of the literature, it was observed that the majority of the papers were from the Participatory Planning Support Systems (PPSS) literature. This finding is not surprising since AI models are digital models that can only exist in information systems such as PPSS. PPSS are valuable tools and processes that promote collaborative decision-making in planning by enabling multiple stakeholders to participate in the planning process. These systems usually leverage digital technologies such as Geographic Information Systems (GIS), simulation models, and web-based platforms to facilitate data sharing, communication, and decision-making. For this reason, our focus would be the recent deep learning methods and the outcomes of the participatory spatial decision-making.

SWOT (Strengths, Weaknesses, Opportunities, and Threats) analysis was chosen as the framework for this systematic review because of its suitability in evaluating complex, multidimensional topics. SWOT provides a structured approach for analyzing internal and external factors that can influence the effect of AI in PPSS. By examining strengths, weaknesses, opportunities, and threats, SWOT allows for a comprehensive understanding of this subject and helps identify areas where improvements can be made or potential risks mitigated.

We conduct the SWOT analysis in the following steps: Firstly, from the 97 papers included in the review, we extracted relevant information on the participatory processes, AI methods, and applications. Secondly, the extracted data were categorized based on the four components of the SWOT framework. Strengths and weaknesses focused on the current state of AI integration in participatory planning, while opportunities and threats considered future developments, potential issues, and external factors affecting the domain. Thirdly, for each SWOT category, the research team reviewed the categorized data, identifying common themes, trends, and patterns. Contradictions, gaps, and discrepancies in the literature were also noted to provide a more nuanced understanding of the topic. At last, the findings from the analysis were synthesized to provide an overview of the current state of AI-enabled participatory planning, as well as insights into potential future developments, challenges, and risks. Recommendations for improving the integration of AI in participatory planning were also drawn from the synthesis.

3. Findings

In Table 1, we present an annotated bibliography of selected case studies, curated based on our assessment of their relevance and contribution. This compilation serves as a reference, detailing the use of various participatory planning procedures and AI methods in urban planning.

Based on the table, the most widely used participatory planning procedures in urban planning include collecting local knowledge, predicting outcomes of alternative plans and facilitating communication. Concurrently, the AI methodologies predominantly employed in these procedures range from diverse optimization and prediction algorithms to natural language processing and computer vision models. In the ensuing sections, we dissect the principal findings utilizing a SWOT analysis framework.

3.1. Strengths

3.1.1. Analyzing local knowledge through big data

Local knowledge is essential for planning. Traditional data were mainly acquired from structured data, such as from the census of population and housing. AI could better understand the fine-scale local environment from unstructured data, such as text and images (Ye et al., 2021). It might provide information to planners about residents' place-based values and land-use preferences in the absence of well-attended community meetings. It could also offer scalability to infer the preferences and needs from a sample representing a much larger group of people. Some unstructured data types include:

3.1.1.1. Offline behaviour data. GPS trajectory data derived from smartphones, credit card records, and records from smart cards in transit systems present the human behaviour in the built environment (Goodchild, 2010). These human behaviour data can reflect the attractiveness and accessibility of places, which can advance our knowledge of the urban environment (Zhu et al., 2020). Various AI models can be designed to learn

Table 1. Example of case studies with both AI and participatory planning (full table see appendix Table A).

Author (year)	Participatory planning procedure	AI methods	Key findings
Walisadeera et al. (2015)	Accessibility of scientific evidence for farmers	Crawler, ontology query system	Enabled knowledge gain for Sri Lankan farmers through a context-aware system.
Miranda et al. (2016)	Project cost prediction	Optimization	Provided initial cost-benefit insights for environmental protection plans in Porto and Brussels.
Shin et al. (2017)	Updating large-scale discussions	CNN, rule-based system, NER	Demonstrated the effectiveness of the eplamier map service in Singapore.
Yu et al. (2017)	Communication facilitation	Best-first Conflict-Directed Relaxation algorithm	Resolved over-subscribed scheduling problems in urban travel planning and transit system management.
Bakht et al. (2018)	Information collection	K-nearest neighbours, Naïve Bayes, Support Vector Machines	Detected community opinion evolution about urban projects through tweet analysis.
Kerebel et al. (2019)	Local knowledge collection	Bayesian networks	Designed a participatory methodology for evaluating landscape aesthetics.
Quan et al. (2019)	Auto-generation of plans	Genetic algorithms, Scientific performance simulation tools	Identified design solutions for sustainable city development in Seoul.
Austin et al. (2020)	Result prediction	Decision Tree	Predicted energy consumption in various scenarios in the Chicago Metropolitan Area.
Liu et al. (2020)	Idea generation	Word2vec	Validated the superiority of AI over wordnet in inspiring design ideas.
Lock & Pettit (2020)	Public opinion collection	IBM Watson Tone Analyzer, VADER, LDA	Found social media as a complementary tool to citizen surveys.
Pournaras (2020)	Witness presence verification	Blockchain consensus	Enhanced participant credibility by recording the decision process in Zurich.
Yang et al. (2020)	Expert identification and water quality monitoring	Adaboost	Developed a model for objective and automatic expert selection and opinion integration.
Haqbeen et al. (2021)	Communication facilitation	Recurrent neural network, Graph neural network	Achieved comparable response rates to human facilitators in an online urban planning forum in Afghanistan.
Kumar et al. (2021)	Communication facilitation	Random Forest	Identified redundant indicators for assessing community sustainability in Kolkata.
Li et al. (2021)	Local knowledge analysis	Decision trees, ensemble learning	Contributed to facilities adjustments and location selections in urban planning.
Lock et al. (2021)	Land value prediction	Xgboost	Found positive attitudes towards AI among planners and developers in Sydney.
Shin et al. (2021)	Communication facilitation	Boosted Classification Tree	Identified factors associated with dispute intensity in multi-owned buildings in Victoria.
Tian et al. (2021)	Satisfaction prediction	Long short term memory neural network	Predicted customer satisfaction for logistic service using simulated data.

from the movement data and predict future traffic conditions (Li, Xia, & Chai, 2021; F. Liu et al., 2020; Schläpfer et al., 2021).

3.1.1.2. Online behaviour data. Social media platforms provide information on space, time, content (text, image, video, voice), and social network connectivity, which would be valuable for understanding citizen preferences within planning (Wang & Ye, 2018). AI models can help extract and analyze user preferences and opinions from the unstructured social media content and other online platforms (Ai, Comfort, Dong, & Znati, 2016; Bakht, El-Diraby, & Hossaini, 2018; Martinez-Lopez et al., 2019; Kaklauskas et al., 2021).

3.1.1.3. Street view imagery. Street-level imagery can be used to measure the human perception of a large-scale urban region (Biljecki & Ito, 2021). Zhang, Wu, Zhu, and Liu (2019) created a dataset from street images labelled with human positive and negative perceptions such as safe, lively, beautiful, wealthy, depressing, and boring; then used AI models to segment street images into green infrastructure and other indicators to describe city features. Planners can thus enhance the design of the target area by taking into account people's perceptions of the area (Zhang et al., 2019).

3.1.1.4. Air quality data. Air quality data have been one of the most important indicators in urban health research (Miranda et al., 2016; Sirbu et al., 2015). Sirbu et al. (2015) adopted the AI models to predict the air quality of cities, showing that direct involvement of community members could enhance environmental awareness.

3.1.1.5. Sound Data. Environmental sound and soundscape have a great impact on the quality of human life (Stamatiadou, Thoidis, Vryzas, Vrysis, & Dimoulas, 2021). AI models have been utilized to forecast the noise levels of upcoming projects and to propose alternative design plans. For example, Stamatiadou et al. (2021) used AI models to automatically label the crowdsourced soundscape data for the heritage preservation planning and recovery process.

3.1.1.6. Building information. AI models help capture the 3D information about built environments from various images, such as reconstructing height information from multiple angles. Aided by this information, equity building design can be realized such as promoting the equitable access to sunlight (Yasumoto, Jones, Yano, & Nakaya, 2012).

These AI techniques can help to provide richer, more nuanced insights into urban environments and community preferences, complementing the costly survey and participatory workshops. These data lay the foundation for participants to discuss design options in the planning process. Knowing the information from the data can make the planning discussion rational and may inspire alternative plans.

3.1.2. Predicting results of alternative plans

One of the strengths of AI is the ability to classify and predict given a sufficient amount of data. As more data becomes available from the current and past planning processes, AI should improve its ability to predict planning outcomes. This adaptability can be particularly valuable in the dynamic and complex context of urban planning. The participatory planning process requires that the alternative plans (planning scenarios) be discussed by stakeholders to reach rational decisions, where the AI prediction power can provide anticipated outcomes and inform the planning decision.

AI models have also been used for predicting the acceptance of alternative plans based on socio-demographic and economic characteristics of urban residents (Dong, Ratti, & Zheng, 2019; Lock, Bain, & Pettit, 2021). Climate change is factor planners need to consider for resilient and sustainable communities (Hu et al., 2018; Lieberknecht, 2021; Meerow & Woodruff, 2020). Abbot and Marohasy (2013) highlighted the benefits of combining multiple non-linear relationships using neural networks to predict weather patterns, which can increase by 10% the absolute value of the prediction accuracy on rainfalls compared with previous models.

Transportation planning is an important domain of urban planning. AI algorithms have improved traffic prediction accuracy by about 20%~50% in Google Maps. AI models demonstrated their effectiveness in helping users resolve over-subscribed scheduling problems and evaluate the robustness of existing solutions for urban transportation planning and transit system management. Those models can better inform traffic planning by incorporating traffic pattern changes (Du, Zhang, Du, & Liu, 2020).

AI models would estimate project costs. Uncertainty in cost estimation is bound to lead to participatory planning project failure (Nijkamp, van der Burch, & Vindigni, 2002). AI models were used to determine a property tax incentive programme eligibility and predict housing value increases based on different planning scenarios in Atlanta, outperforming traditional hedonic methods in prediction accuracy (van den Homberg, Gevaert, & Georgiadou, 2020). The community members were invited to discuss and provide information and opinions about the programme, which increased the estimation accuracy of the model and validated the modelling, leading to a novel integration of AI and participatory planning. By altering the input variables and inspecting the model output, planning participants can improve financial policy (Nousdilis et al., 2020). The co-design model in the participatory planning system allows users to discuss and annotate the prototype before being exposed to all the interactions available in the fully developed systems (Lock et al., 2021).

AI models could also be used for recommending alternative plans to acheive multiple goals. Molina (2005) created an AI-based intelligent assistant for simulating the transportation decision process in Torino (Italy) and Vitoria (Spain), including diagnosis, prediction, and planning. The model supports generating feasible measures (e.g. financial support, zoning regulations) to accomplish the optimum long-term plans by formulating the planning problem in a mathematical format. Zhang et al. (2018) developed the CityMatrix to let non-experts change land-use patterns and predict the corresponding traffic scenario. Using social media to communicate with residents, the output of AI models informs participants of the possible consequences of alternative emergency management plans (Ai et al., 2016).

3.1.3. Relieving the burden of plan generation

Besides the potential to generate alternative plan scenarios, AI models can partially automate the plan generation. This automation lowers the cost of participatory planning, making participation affordable even for low-income communities.

Urban planners can adopt AI models to generate maps of planned changes. For example, Yu, Zhang, Li, Montenegro-Marin, and Kumar (2021) designed an AI model that optimized the logistics in a waste management system with multiple stakeholders, improving the planning and management performance, accuracy, and efficiency. Given the site boundary and the number of buildings, Dehaene (2020) designed a model based on the ant colony optimization algorithms to automatically arrange the site planning by minimizing safety concerns and reducing construction costs. Participants can change the constraints or requirements based on the auto-produced plan to quickly see the revised plan, achieved by coevolutionary and genetic algorithm-based methods in such automated planning support systems (Quan, Park, Economou, & Lee, 2019). The AI provides the ability to maintain spatial relations among the plan's structural elements as the design diagram is transformed, to recognize 'emergent' patterns and configurations in a diagram, to perform transformations that carry one diagram to another, to identify similarities and differences among diagrams, and to represent designs at varying levels of abstraction and detail (Do & Gross, 2001).

AI models can also retrieve relevant data to inspire designers (Q. Liu et al., 2020), making it possible to learn stylistic design criteria from existing urban designs and/or landscape architectural designs and transfer these styles to other designs. Ye et al. (2021) developed an AI model that can automate the process of colouring masterplans and quickly make changes to the result. These applications learn the transfer patterns between the source and target data in the training process and then automatically apply them to a similar dataset.

3.1.4. Facilitating communications between stakeholders

Providing more information and reducing the plan costs support participatory planning in a general way, as these AI abilities would benefit the broader planning practice. There are also specific benefits of using AI in participatory planning. Auto-transcript and auto-translation services in online meetings can enable easier information access for other language speakers and people who need hearing aids (Tomašev et al., 2020). Here we discuss some detailed examples of how the integration of AI technology with a planning information system can facilitate communication between stakeholders.

The selection of participants is usually the first step in participatory planning. Ideally, the participants would encompass all stakeholders including residents affected by the proposed plan, professional planners, representatives of local government agencies, community leaders, consultants, and experts (Rodriguez-Soto, Velazquez, Monroy-Vilchis, Lemes, & Loyola, 2017). Yang et al. (2020) classified the experts' professional level by developing a machine-learning algorithm based on the indicators such as professional title, age, education degree, the field of expertise, number of published papers, and number of patents. The output of the AI model was used to identify the domain experts and how expert opinion should be weighted in the final decision.

When analyzing nine urban land-use and revitalization projects in the Netherlands, Nijkamp et al. (2002) found a public-private partnership based on the joint-venture model has a higher chance of success. The participants first came up with many indicators for assessing the sustainability of communities, then they used the AI model to identify the redundant indicators (Kumar, Bhaumik, & Banerji, 2021). Escobedo, Bottin, Cala, and Montoya (2020) employed the AI model to assess different stakeholders' abilities in recognizing various landscape processes, and to design more context-relevant survey instruments for participatory planning.

AI models would extract the significant information nuggets from the participant's input and update those involved in the discussion. Topic modelling summarizes the main themes contained in user posts. Sentiment analysis models distinguish people's attitudes (i.e. positive or negative) towards specific policies. Shin, Rajabifard, Kalantari, and Atazadeh (2021) built a machine learning model to predict the level of property disputes. AI models can map the place mentioned by the participants, providing the spatial context for a discussion (Shin, Yuan, Siong, Zhang, & Phang, 2017).

AI models also could encourage people to share opinions. For example, the recent success of deep learning-based large-scale language models significantly boosts the performance in many languages understanding tasks such as reading comprehension, question answering, and chatbot systems (Brown et al., 2020). This enables AI such as a chatbot to automatically generate the most plausible response given a context. By responding to the reported issues by participants in the online forum, the chatbot can mediate the discussion by posting meaningful messages and replying to user posts based on the pre-defined answers (Haqbeen et al., 2021). Public participation experiments in urban planning in Afghanistan showed that the AI facilitator could achieve almost the same response rate as the human facilitator. Furthermore, AI paired with Blockchain technology can enhance the credibility of participants by recording the participatory process (Pournaras, 2020).

In addition to building trust by improving the credibility of participants, AI models can synthesize the discussions and help people reach the consensus with decision models if every participant agrees on a standardized decision procedure. There is a rich literature about standardized group decision models based on brainstorming, voting, and ranking (Jankowski & Nyerges, 2001; Jelokhani-Niaraki, 2021). Agent-based models can be used to predict the voting results (Aguirre & Nyerges, 2014). By changing the behaviour of automated agents, an alternative decision process pathway might be discovered.

3.1.5. Educating participants with scientific evidence

One benefit of participatory planning is shared understanding developed by all parties through communication and collaboration. If public participation is intended to produce systematic changes, all stakeholders need equal and equitable access to data and information resources (Rosen & Painter, 2019). AI models can make scientific evidence more accessible to the public involved in planning. Professional planner can use scientific evidence to inform the general public. For example, Walisadeera, Ginige, and Wikramanayake (2015) developed an AI model to automatically collect knowledge from government websites, agriculture department leaflets, and radio and television programmes on agriculture for Sri Lankan farmers, enabling them to defend their interests.

Access to more information can boost the participation rate. After informing the public in detail, the participation rate increased by 3%∼17% in the household hazardous waste collection and recycling programme. Lim-Wavde, Kauffman, and Dawson (2017). People involved in the community decision procedure gained access to scientific and technical guidance because they volunteered to collaborate with a local university and reach the disadvantaged community members (Girbes-Peco, Renta-Davids, De Botton,

& Alvarez-Cifuentes, 2020). AI models also helped participants to understand science (Rivet & Krajcik, 2004) and increased their environmental awareness (Sirbu et al., 2015).

3.2. Weaknesses

3.2.1. Lack of documentation on AI's impact on group processes and outcomes

Although there are claims in the literature about the usefulness of AI in participatory planning, very few of them document how the technology changes group process and outcomes. The goal of participatory planning is to empower community members by allowing everyone to contribute spatially-explicit values, preferences, and experiences to the decision making process Most of the reviewed papers in Table 1 (and appendix Table A) described methods and their use in a participatory process but stopped short of reporting on how the used methods affected the decision making.

3.2.2. Data sampling biases

Looking at the AI methods, data sampling biases are a major concern because data shape the machine learning models. Incorrect or biased data leads to useless interpretation and analysis. The data and information contributed by participants may suffer from various biases including demographic, education, and spatial imbalance (Ibrahim, Khodursky, & Yasseri, 2021). The neighbourhoods with limited infrastructure and low-income populations produce relatively small amounts of digital signals in comparison to more affluent neighbourhoods (Long, Zhai, Shen, & Ye, 2018). Researchers should consider these data biases when collecting the data.

3.2.3. Lack of causal explanation in deep learning methods

New deep learning methods can boost prediction and simulation performance. However, most of them cannot explain the causal relationships among variables, making some prediction models difficult to be applied in planning practice. For example, the population is always a crucial independent variable in the housing price prediction model, but housing and population are co-dependent. Causal machine learning methods have a great potential to help planners and participants to understand the causal structure among different variables. Those methods would generate a series of possible causal relationships between the variables, then score the possibilities with a variety of methods or ran independent tests to get the most possible causal relation (Schölkopf et al., 2021).

3.2.4. Limited familiarity with AI methods

However, planners and urban researchers may not be familiar with AI methods. There still are challenges in sharing and using new data and methods across disciplines, as many argue that urban planning is siloed and lacks common methodology. For example, architects and planners infrequently collaborate in educational programmes (Malczewski & Jankowski, 2020). Urban planning education typically does not equip future practitioners with AI knowledge. AI-focused education should be added to urban planning curricula to prepare future planners for using AI techniques in planning practice and communicating about their results with the public.

3.2.5. Resource constraints

Limited resources in the planning field are another constraint. Municipal planning offices typically have limited budgets and tight work schedules to accomplish planning processes such as plan designs, public and stakeholder consultations, and institutional approvals. The extra costs of adopting AI technology in participatory planning need to be justified. The AI application costs include the software license fees and the hardware needed to deploy the application (Kontokosta, 2018). An AI chatbot usually charges its customers based on user numbers and provides only specific language services (Haqbeen et al., 2021). In addition, the code of online forums was developed with different programming languages, requiring multiple technicians to maintain. Planners may find it hard to adopt new AI technologies because of their lack of expertise and funding.

3.2.6. Ethical considerations

The use of AI in decision-making also raises ethical considerations. The potential for AI to perpetuate existing biases, unequal power relations, and exclusionary practices calls for careful consideration of the ethical implications of AI use in participatory planning (Gorodnova et al., 2020; Falco 2019; Cai et,al 2018). Ensuring transparency, accountability, and inclusivity in AI decision-making processes is crucial to promote more equitable and sustainable outcomes.

4. Discussion

The integration of AI in participatory planning has sparked a discourse on its comparative efficacy against traditional technocratic and authority-led models in local decision-making. Advocates posit that AI fosters a more transparent, inclusive, and accountable decision-making process by empowering diverse stakeholders to participate and share their knowledge and preferences. Conversely, critics caution about the potential for AI to reinforce existing biases, power imbalances, and exclusionary practices. Therefore, it is crucial to weigh the advantages and risks of AI in participatory planning, and to investigate how these systems can be designed and implemented to advance more equitable and sustainable outcomes. The insights presented in this section are derived from a systematic literature review, as summarized in Table 1, and they form the basis for our detailed discussion on the opportunities and threats of AI in PPSS.

4.1. Opportunities

Beyond the integration issues, we look for opportunities in planning and the AI research community to advance participatory planning further. How might advancements in AI research be applied to participatory planning? How does the development of planning theory and practice guide AI integration? We tackle these questions in this section.

The development of plans demands extensive knowledge of different technical and scientific domains and the comprehension of interactions between these domains (Austin, Delgoshaei, Coelho, & Heidarinejad, 2020; Jankovic & Zarate, 2011). It requires the collaboration of planning experts and stakeholders (Jankowski & Nyerges, 2001), which would be a core element in participatory planning. For example, climate planning asks for knowledge about environmental health, urban heat planning, and climate-related land use planning (Lieberknecht, 2021).

Recent advances in knowledge graphs have the potential to address the interdisciplinarity challenges. The vast heterogeneity of the disciplines involved in participatory planning ranging from the natural sciences to the social sciences (e.g. meteorology, environmental planning, urban planning, human geography) demonstrates new challenges in terms of data accessibility, reusability, and interoperability while geospatial semantics and knowledge graphs have the potential to overcome these challenges (Mai, Janowicz, Cai, et al., 2020, p. 2). A knowledge graph is a form of data representation that connects pieces of information together. In a knowledge graph, nodes represent entities (like people, places, or things), and edges represent relationships between these entities. For example, in a knowledge graph about a planning department, nodes might represent employees, departments, and projects, while edges might represent relationships like 'works in' or 'manages'. Knowledge graphs are used in many applications, including search engines, recommendation systems, and AI systems, because they provide a structured, easily understandable way to represent complex relationships. Knowledge graphs have shown promising results in data integration & geographic entity alignment (Du, Wang, Ye, Sinton, & Kemp, 2021), geographic question answering (Mai, Janowicz, Yan, et al., 2020), and others. Utilizing knowledge graphs would be a possible solution to overcoming the interdisciplinarity challenge by providing a common knowledge base for planning. The ability to inform decision makers from the participatory planning process would be the key to overcome various bias (Innes & Booher, 2018).

Numerous AI models are freely accessible on the internet for planners to harness. They often provide user-friendly interfaces, such as that of ChatGPT(chat.openai.com), making these models readily usable without any financial cost. While it is important to take caution when using such models because those model are not open and they may try to collect sensitive information. Efficiently designed AI tools streamline the user experience by abstracting the intricate technical details. This approach makes AI capabilities more accessible, as it does not necessitate users to have extensive AI knowledge.

Not only many AI models are free, but also many models and their data are open sourced, as many developers choose to open-source their code on platforms like GitHub (www.github.com). This open policy tradition within the AI community not only democratizes access to both information and analytical tools but also fosters a larger pool of contributors, encouraging a wider range of ideas. This, in turn, facilitates continuous improvement and potentially catalyzes innovations in theory and practice (Wang & Ye, 2018). The transparency inherent in open-source AI models and data is unique. Unlike human actors, AI models ideally do not hold personal interests, and their decision-making processes are based solely on the data and algorithms they are trained on. This transparency can build trust among collaborators, as they can verify the data and algorithms used in the decision-making process. This trust, coupled with the shared understanding of the resources at hand, may foster cooperation and facilitate collective problem-solving.

The development of quantitative methods for evaluating diverse plans enhances the application of AI. This concept is illustrated in the work of Berke & French (1994), where plan quality was assessed based on three aspects: (1) factual basis, (2) clear and comprehensive goals, and (3) action-oriented policies. Additional elements, such as plan implementation actions, monitoring strategies, inter-governmental coordination, and participation, were later incorporated (Berke et al., 2012). Rule-based models have already been utilized to verify whether a plan adheres to regulations for fire safety and yard setback requirements (Heikkila & Blewett, 1992). While these models can be effective in certain contexts, they also have limitations. For instance, they may oversimplify complex planning issues, overlook contextual nuances, and struggle to adapt to changing circumstances. However, with more attributes of plan quality are expressed in a mathematical format, AI models can capture more aspects of the plan and environment, thereby automating the evaluation of planning.

Falco (2019) introduced the concept of participatory AI, envisioning the use of blockchain technology to ensure transparency in AI applications within smart cities. For example, the text mentions that if the community had commented on the algorithm behind the AI for the Chicago Police Department's 'strategic subject list', the AI could have been less biased and more socially responsible. This technology provides a historical record of comments that remains accessible for future scrutiny of the AI's decisions. Such emerging technologies could potentially bolster confidence in the transparency and security of future participatory planning practices.

4.2. Threats

Applying AI in participatory planning faces threats, many of which are beyond the planners' control. Some fear that key individuals, including proponents and opponents of a plan, might game the system to achieve their ends. Some critics argue that participatory planning can be manipulated so it will only benefit powerful people. For example, automated social media accounts can be used to influence the land development and planning process by generating 'an environment in which distortions were propagated' (Hollander, Potts, Hartt, & Situ, 2020).

Applying AI in participatory planning faces **legal challenges** such as privacy agreements and accountability. The popular social media platform, Twitter, puts constraints on its policy for collecting user information, requiring detailed plans provided by any researcher who hopes to analyze the user-generated content. Still, people would worry their privacy might be revealed by AI models (Walter & Scholz, 2007; Wang & Ye, 2018). While humans traditionally held responsibility for their decisions, the advent of AI has introduced a potential shift in this dynamic, with individuals potentially attributing poor decisions to these technologies. This raises significant concerns about accountability, particularly among politicians (van den Homberg et al., 2020). Despite AI's ability to perform certain tasks akin to humans, it is crucial to remember that ultimate decision-making responsibility still resides with humans.

The use of AI in planning poses the question of whether anyone would willingly surrender decision-making power in whole or in part to a machine. Put differently, can people trust AI? This is expressed in two distinct ways – people may think technology is **unreliable** or they may **overtrust** the machine. We found assertions in the literature suggesting that the general public welcomes various AI applications (Fagerholm et al., 2021; Lock et al., 2021; Sirbu et al., 2015).

However, skepticism may arise among non-experts when planners are unable to explain a model or adjust their expectations accordingly. In those cases, the AI models are an un-explainable black box (Frazier, Wikle, & Kedron, 2018). Research on explainable AI sheds light on a potential solution but still faces theoretical challenges (Slack, Hilgard, Jia, Singh, & Lakkaraju, 2019). Analyzing how humans build trust toward each other would also help to find ways for people to trust AI (Gillath et al., 2021).

Generally, AI models are very complex, and many are not mature. The short life of technology and a relatively small number of application domains cannot provide enough evidence for efficiency and good performance, making it difficult for people to build trust in AI systems. The **reproducibility and replicability** of the empirical studies of integrating AI with planning are problematic. Unlike algorithms, whose accuracy can be readily improved through data refinement and code optimization, replicating human behaviour in a participatory planning workshop presents a significant challenge (Wilson et al., 2021). This complexity arises from the unique characteristics of each individual and the constantly evolving dynamics of social interactions, both of which warrant further research.

Many deep learning models have been experimentally incorporated within the planning process as individual components, yet a plan created entirely by AI remains unseen. While AI can assist planners by facilitating the development of alternative designs, it cannot supplant planners in the current stage of AI development when it comes to creativity and understanding the physical, social, legal, and political characteristics of areas subject to planning practice. The integration of AI and participatory planning is still in its nascent stages, with only a handful of case studies addressing real-world planning problems identified in our literature review, such as those by Haqbeen et al. (2021), Lock et al. (2021), Auerbach et al. (2020), and Escobedo et al. (2020).

6. Conclusion

The manuscript's contribution is to review recent deep learning methods and their outcomes in participatory spatial decision-making. The state of the current practice of AI in participatory planning can be characterized as an early stage of integration between the two fields. Our analysis showed the strengths of AI in participatory planning include collecting more local knowledge through unstructured data, facilitating communication between stakeholders, educating participants using scientific evidence, predicting results of alternative plans, and automating plan generation. The weaknesses of the AI models in participatory planning include the data sample bias, lack of the ability to model causality, and the costs of education, software, and hardware.

We identified opportunities for several potential applications in participatory planning based on the recent advances in planning and AI. For example, new deep learning models and knowledge-graph-driven applications can support planning decisions. New sources of data offer more information on the target participants, setting up a rich empirical context for urban research and policy interventions. Automated plan evaluation tools are enabled thanks to quantitative planning evaluation research and lay participants can be supported in contributing preferences and local knowledge by AI-enabled design tools. Lastly, we discussed the threats to the integration including the barrier of the digital divide, model trustworthiness, privacy issues, and algorithm accountability as serious impediments to progress in embedding AI in participatory planning.

This systematic literature review has surveyed recent publications on AI and participatory planning. Yet, due to the rapid development of both fields, some studies might have been overlooked. The field emerging at the intersection of planning and AI calls for more synthesis efforts and a comprehensive framework to realize the potential benefits of the synergy of participatory planning. Future research should focus on ways of making AI an ethical and trustworthy urban infrastructure asset rather than an adversary fraught with controversy and bias.

Data and codes availability statement

As this is a review paper, data and codes do not apply.

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Appendix

One graph summary of the paper

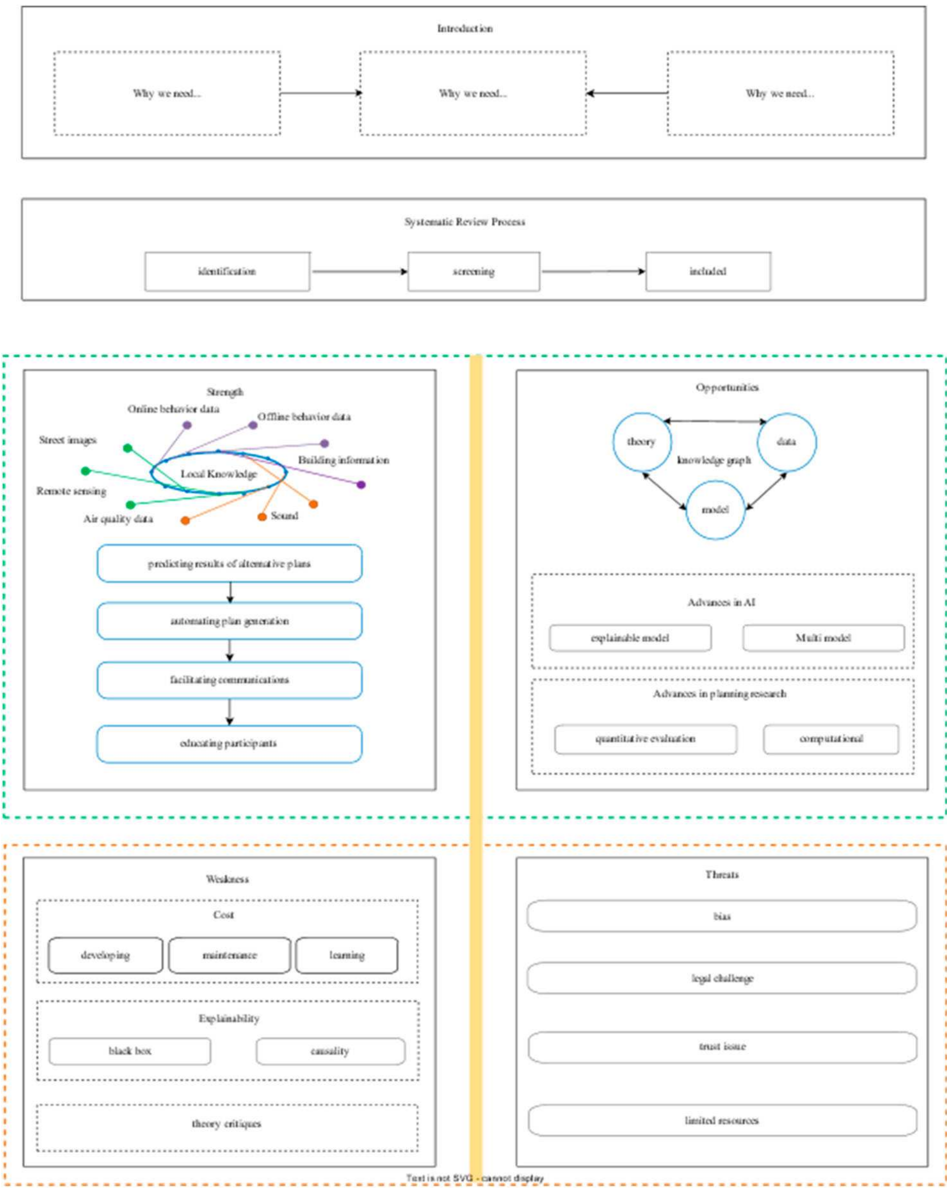

Figure A. Summary of this review

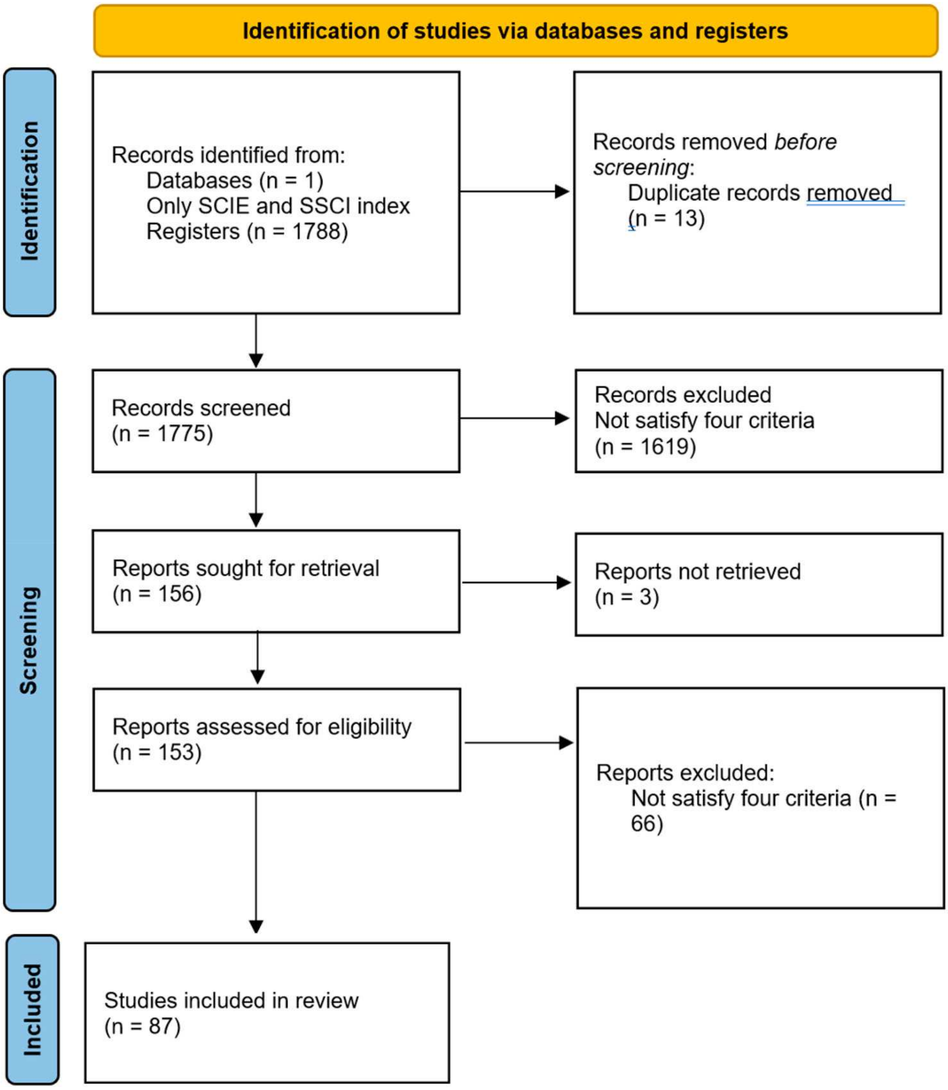

Figure B. Systematic review workflow (after Page et al., 2021).

Review method

The search query on the web of science:

> (((ALL = (artificial intelligence) OR ALL = (machine learning) OR ALL = (AI) OR ALL = (deep learning)) AND ((ALL = (participatory) OR ALL = (collaborative) OR ALL = (group) OR ALL = (community) OR ALL = (public) OR ALL = (stakeholders) OR ALL = (involvement)) AND ((ALL = (spatial) OR ALL = (geographical) OR ALL = (geospatial) OR ALL = (location) OR ALL = (gis) OR ALL = (land) OR ALL = (site) OR ALL = (urban)) AND ((ALL = (planning) OR ALL = (decision making) OR ALL = (design))))))

We retrieved 1788 papers from the database. Automated software was employed to remove 13 duplicated records, resulting in 1,775 unique publications. These publications were then screened for relevance by examining their titles and abstracts. The majority of the papers were found to be missing one or more groups of keywords from our four components and were subsequently removed from the review list, leaving 158 papers. These selected papers were carefully reviewed to collect information about the use of AI in participatory planning processes. We excluded papers that focused only on micro-level topics, such as interior house design or neighbourhood recommendations without citizen input. Additionally, we removed studies that solely provided results to persuade community members rather than gathering opinions from the community. While there has been a significant body of research focusing on spatial decision support systems, relatively fewer research efforts have been dedicated to the use of these techniques in collaborative contexts.

After thoroughly examining the full text of the remaining papers, we identified 87 relevant publications. To ensure comprehensiveness, we scrutinized the reference sections of these publications for additional studies related to our topic. This process led to the inclusion of 10 more conference papers from AI conferences, bringing the total number of reviewed papers to 97. The final dataset comprises review papers, opinion papers, and 45 empirical papers documenting specific use cases in the realm of AI-enabled participatory planning. Figure B presented our systematic review process.

Full annotated bibliography table

Table A. Full annotated bibliography of case studies with both AI and participatory planning in chronological order.

Author(year)	Participatory planning procedure	AI methods	Findings
Do and Gross (2001)	Designs at varying levels of abstraction and detail	Image processing algorithms	The paper identified requirements for computational support for the diagrams in design thinking.
Nijkamp et al. (2002)	Identify successful experience for participatory planning	Rough set analysis	Using an AI model to analyze nine Urban Land-use and Revitalization projects in Netherlands, the authors found a Public – Private Partnerships arrangement has a high chance of becoming successful, if it is designed based on joint-venture model.
Yasumoto et al. (2012)	Collecting local knowledge about building height	3D analysis	Aided by the building height information, building design and city planning can improve equity in the access to sunlight
Walisadeera et al. (2015)	Made scientific evidence more accessible for Sri Lankan farmers	Crawler, ontology query system	Sri Lankan farmers can gain knowledge in this context aware system.
Ai et al. (2016)	Selecting leaders to pass out the alert, Predicting the possible consequences of alternative emergency management plans	Optimization (heuristic algorithm)	The AI system has potential to support evacuation strategies and real-time guidance of communities at risk during disaster.
Miranda et al. (2016)	Predicting project costs on different scenarios	Optimization	In Porto Region and Brussels Capital Region, the models allowed stakeholders to have a first idea of the optimal investment costs and benefits in the environment protection plan. The author also found that the tools should be extended to allow their users to consider the implications of political and social acceptance in an early stage of the decision process.
Rodriguez-Soto et al. (2017)	Predicting stakeholder's willingness to corporate	Artificial intelligence ensemble model	Agrarian communities that have coexisted for millennia with umbrella species can be regarded as allies in biodiversity conservation

(*Continued*)

Table A. Continued.

Author(year)	Participatory planning procedure	AI methods	Findings
Shin et al. (2017)	Keep everyone updated in a large-scale discussion by automatically enriching plan with geographical insights	CNN, rule-based system and NER	Results are presented on the eplamier, which is a map service on the GIS implemented by the urban redevelopment authority of Singapore.
P. Yu et al. (2017)	Facilitating communication by identifying temporal scheduling problems	Best-first Conflict-Directed Relaxation algorithm based on Conflict-Directed A* Algorithm	It has demonstrated its effectiveness in helping users resolve over-subscribed scheduling problems and evaluated the robustness of existing solutions for urban travel planning and transit system management.
Bakht et al. (2018)	Collecting information	K-nearest neighbours, Naïve Bayes and Support Vector Machines	Using AI to analyze tweets helped detect the evolution of community opinion about urban projects
Sharma et al. (2018)	Predict climate change	Integrated model of atmosphere, land, and lake	The authors stress the need to include input from diverse stakeholders in the development of tools to ensure the quality and usability of impact assessments.
Zhang, Grignard, Lyons, Aubuchon, and Larson (2018)	Predict the traffic based on different land-use patterns	Agent-based model	The result is a versatile, quick, accurate, and computationally efficient approach to provide real-time feedback and optimization for urban decision-making.
Barbosa et al. (2019)	Predicting results of alternative plans	Random Forest, Boosted Regression Trees and Maximum Entropy	Stakeholders define the problem and choose restoration and conservation plans in Andalusia (Spain) – Morocco based on results predicted by AI model
Elizalde-Ramirez et al. (2019)	Predicting results for alternatives transportation plans	Integer mathematical programming	The analysis identifies user preferences as the most critical factor that increases solution complexity for planning models.
Kaklauskas et al. (2019)	Collecting local knowledge to give tips for stakeholder groups.	Computer vision to detect emotions and demographical information	Can assist public spaces planning and a participation process by attendees by collecting and examining the emotional and physiological parameters of visitors.
Kerebel et al. (2019)	Collecting local knowledge about Landscape aesthetic	Bayesian networks	A participatory methodology for evaluating landscape aesthetics was designed to weigh indicators according to stakeholder preferences,
Martinez-Lopez et al. (2019)	Collecting ecosystem services of interest from stakeholders, then participants make plans with synthesized opinion	General linear models	The human-AI co-developed solutions can support adaptive management and the conservation of coastal ecosystems in Portugal.
Quan et al. (2019)	Auto-generate plans in a superblock based on participants input	Genetic algorithms, Scientific performance simulation tools	The case study in Seoul, South Korea illustrates how the framework identifies design solutions for sustainable city development in the process of participatory decision-making.

(*Continued*)

Table A. Continued.

Author(year)	Participatory planning procedure	AI methods	Findings
Zhao et al. (2019)	Explore nonlinear relationships between agent behaviours and decision-making environments and efficiently identify solutions to land use allocation in a spatially explicit way	Agent-based model and heuristic methods	The optimal allocation solutions obtained by the agent-based model are more applicable based on the support of the factual evidence than those obtained by the non-agent-based model. The proposed model can integrate the simulated local decision of stakeholders and global optimization of the specified objectives in land use planning, and thus provide a flexible theoretical framework to support the reform of China's spatial planning system.
Y. Hu et al. (2019)	Collecting local knowledge	Sentiment analysis, topic modelling	This research was applied to New York City community reviews to support urban planning
Auerbach et al. (2020)	Budgeting	Random Forest	Data collected from residents can also correct and update the information, which would increase the accuracy of the programme estimates and validate the modelling, leading to a novel integration of AI and participatory planning
Austin et al. (2020)	Predicting results from alternative plans	Decision Tree	They used AI models to predict the energy consumption with several scenarios in the Chicago Metropolitan Area
Escobedo et al. (2020)	Assess the ability of different stakeholders	Classification and Regression Trees	This study used an AI model to identify and assess different stakeholder's abilities in recognizing different processes from landscapes as well as their difficulty in accurately locating areas of interest. Low cost and participatory approaches can be used to design more context-relevant survey instruments for ecosystem service valuation research and assessments
Liu, Wang, Li, and Liu (2020)	Comparative analysis of recommended candidate warehouses.	Matrix-factorization and rule based algorithms for processing data	A case study in Shanghai, China, confirmed the efficacy of the system
Liu et al. (2020)	Inspire designers' idea generation	Word2vec	Their demo validated that the AI method is better than wordnet for inspiring designers to generate design ideas.
Lock & Pettit (2020)	Ask people's opinion on social media	The IBM Watson Tone Analyzer, VADER, LDA (Sentiment analysis and topic modelling)	Social media can be complementary to citizen surveys due to the sample and the techniques limitation
Nousdilis et al. (2020)	Assess the impact of various incentive policy schemes and operation strategies on the economic viability	Techno-economic modes based on an exhaustive optimization search	The results can be a valuable guide for policymakers and the market regulators to design new incentive schemes
Pournaras (2020)	Proving witness presence	Blockchain consensus.	The testnet scenario in Zurich showed that the model can enhance the credibility of participants by recording the decision process
van den Homberg et al. (2020)	Trigger the release of funds typically used for humanitarian response in advance of an impending typhoon to start up early actions to mitigate its potential impact.	Random forest and artificial neural networks	They highlighted emerging actors and fora in the accountability relationship of anticipatory humanitarian action as well as the consequences arising from actors' (mis)conduct.

(*Continued*)

Table A. Continued.

Author(year)	Participatory planning procedure	AI methods	Findings
Yu et al. (2021)	Environmental planning, gathering local knowledge, garbage volume prediction, optimize waste collection	Multiple optimization algorithms	Their model helps collect information from multiple stakeholders and improving environmental planning and urban management performance, accuracy, and efficiency in Dongguan City, China.
Yang et al. (2020)	Identify experts. Monitoring water quality	Adaboost	A model was developed to select experts and integrate opinions objectively and automatically for governance alternatives in Yuyuantan Lake Beijing, China
Haqbeen et al. (2021)	Facilitating communication (content labelling, document summarization, and sentiment analysis in online forum)	BERT, recurrent neural network, Graph neural network,	The AI facilitator in online forum for urban planning in Afghanistan achieve almost the same response rate as human facilitators.
Kaklauskas et al. (2021)	Studies local knowledge such as emotional, affective, and physiological states, arousal and valence of the passersby.	Neuro decision matrix, which assisted in deriving a comprehensive analysis of the urban areas	The affective system for researching emotions was proven a helpful supplement to urban planning and public participation practice in the Vilnius city, Lithuania.
Kumar et al. (2021)	Facilitating communication	Random Forest	The participants first came up with many indicators for assessing the economic-socio-cultural sustainability of communities in Kolkata, India, then used AI model to identify the redundant indicators.
Li et al. (2021)	Analyzing local knowledge about human behaviour	Decision trees and ensemble learning	The proposed method and delineation results contribute to facilities adjustments and location selections in life circle planning, people-oriented transformation in urban planning.
Lock et al. (2021)	Predicting changes in land value based on different planning scenarios	Xgboost	In the workshops in Sydney, Australia, general attitudes towards artificial intelligence for planners and developers were positive, as they were seen as both potentially transformative but also as simply another technique to assist with workflows.
Shin et al. (2021)	Facilitating communications by understanding and predicting disputes	Boosted Classification Tree	Using the dispute cases in Victoria, Australia, this research confirms six factors highly associated with the dispute intensity in multi-owned buildings.
Shuler et al. (2021)	Predicting the change of water resources based on alternative land-use plans	Soil Water-Balance-2 model, dynamically downscaled general circulation climate model	Using future land use proposed by local stakeholder group, the model predicted future sustainability of essential resources in Tutuila Island, American Samoa.
Stamatiadou et al. (2021)	Collaborative collection and documentation of soundscapes and environmental sound semantics	A feature-based machine learning network and a convolutional deep learning architecture for sound classification	The AI models automatically labelled the crowdsourcing sound scape data for heritage protection, making the data management easier.

(*Continued*)

Table A. Continued.

Author(year)	Participatory planning procedure	AI methods	Findings
Tian et al. (2021)	Predicting satisfaction of alternative plans, making compensation to those unsatisfied customers	Long short term memory neural network	They used simulated data to predict customer satisfaction for logistic service. A smart contract based on block chain was designed to increase the transparency and protect sensitive information between logistics enterprises and the third authorities like banks and governments.
Ye et al. (2021)	Colorize master plans	GAN	The user cannot distinguish which master plan was generated by computer.