Resilience Development Initiative

The Complexity of Urban Planning and AI Role in Shaping Cities

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Introduction of New Approach of AI in Urban Planning

In the dynamic realm of urban development, Artificial Intelligence (AI) stands out as a transformative force with the potential to revolutionise city planning. AI emerges as a promising solution as cities grow more intricate and interconnected and face challenges like traffic congestion and environmental sustainability. By leveraging data-driven insights, AI can optimise resource allocation, improve decision-making processes, and contribute to the development of smarter, more sustainable urban spaces. However, this transformative shift necessitates a fundamental reevaluation of the roles of urban planners, who evolve from architects of spatial design to interpreters and orchestrators of the data-driven symphony that AI offers. Effective integration involves collaboration between data science, technology, and community engagement experts, ensuring that AI insights are interpreted and applied while prioritising ethical considerations to prevent the exacerbation of social disparities.

This article explores the multifaceted roles of AI in urban planning, how cities can harness new technologies in their decision-making processes, and how numerous urban centres are already embracing this innovative approach in their day-to-day operations. The journey towards AI-augmented urban planning promises progress but raises ethical and practical questions. It is crucial that we, as a society, not only embrace AI's potential but also navigate its implementation with mindfulness, inclusivity, and the enduring goal of creating equitable and sustainable urban environments for all.

Implementing AI in Urban Planning: An Artificial Intelligence-Aided Design (AIAD)

Quan et al. (2019) developed a Smart Design framework (Figure 1) that mainly focuses on urban design decision-making by involving artificial intelligence-aided design (AIAD) and several relevant participants, and the framework mainly focuses on the urban design process. Four distinct groups of experts are involved in the design project: the public group (including citizens), the design group (designers, engineers, and computer scientists), the regulation group (government agents), and the implementation group (developers and banks). They collaborate and contribute their knowledge and concerns, similar to the concept of urban living labs. The Smart Design framework is characterised by a dynamic and iterative structure consisting of four internal loops instead of a simple sequential model of four stages. These loops facilitate the co-evolution of design problems and solutions, supporting complex and ill-structured design activities.

The Smart Design framework consists of two closely connected parts: processes and participants. The processes comprise two design processes: a general design process that facilitates the co-evolution of design problems and solutions and a narrow design generation that employs AI techniques and computational tools to address well-defined design problems. The general design process views urban design as an emergent pattern-formation process with evolving objectives across various systems. It includes four major stages: human problem initialisation, human-system interface, system optimisation, and human-system interaction.

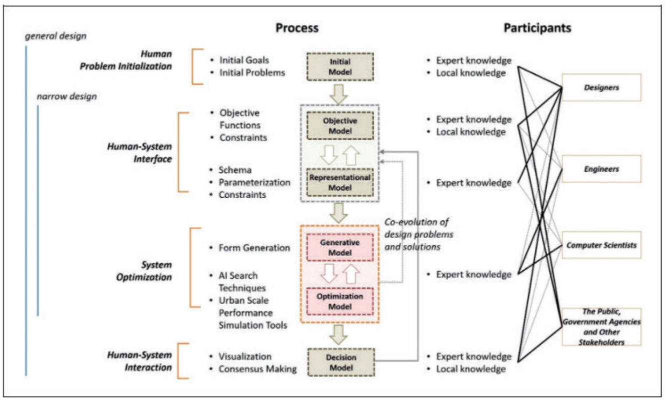

Figure 1. Smart Design Framework
Source: Quan et al., 2019

The Smart Design framework encourages collaboration between participants and employs advanced AI techniques to enhance the efficiency and effectiveness of urban design processes. The process of implementing AIAD operates as follows (**Table 1**):

Table 1. Models and Participants in Four Stages of Smart Design Framework

Stages	Model	Process
Human Problem Initialisation Stage	The design begins with an initial interpretation of the design problems and goals.	At this stage, experts focus on the way humans solve problems to identify challenges like traffic congestion and downtown public space
Human-System Interface Stage	Design problems from the first stage are encoded into mathematical representations, creating objective functions and identifying related constraints.	Designers and computer scientists collaboratively create abstract urban representations with numerical parameterisation and coded constraints.
System Optimisation Stage	Design variations are generated based on parametric representation and constraints. Designs are further parsed into geometric and semantic objects.	Applies AI search techniques like genetic algorithms and scientific simulations to find optimal solutions based on performance criteria, integrating design, engineering, and computational expertise.
Human-System Interaction Stage	System optimisation results are visualised in 2D, 3D, or virtual environments using tools like CityScope for informed decision-making.	All stakeholders, discuss using visual and semantic representations to select optimal designs and refine objectives and constraints for iterative design.

Source: Authors, extracted from Quan et al. (2019)

However, effective integration encounters challenges due to disparities in data transparency and government transparency between developed and developing cities. The effectiveness of AI applications in urban planning is contingent upon cities possessing comprehensive digital data coupled with robust corporate governance and transparent government practices. The complexity of urban governance is heightened by factors such as population growth and digitalisation.

However, the realisation of urban digitalisation may face challenges, particularly in regions with existing tendencies that hinder its adoption, potentially delaying the overall uptake of digital solutions and impacting urban efficiency (Qurbonova et al., 2023).

Orchestrating the Symphony: Integrating AI into a Complex Role of an Urban Planner

Urban planners have long been the stewards of city development, employing a blend of creativity, policy understanding, and community engagement to shape urban spaces. With the advent of AI, their role has become more intricate, bridging the gap between technology and society. AI augments planners' capabilities by analysing vast datasets, predicting urban trends, and simulating scenarios. This newfound computational power allows planners to make informed decisions regarding zoning, infrastructure development, and environmental conservation. However, as AI assists in the technical aspects of planning, planners must focus on their human expertise: interpreting AI-generated insights, ensuring public participation, and embedding ethical considerations in the decision-making process. Son et al. (2023) highlight several practices of AI usage in urban planning listed in the table below:

Table 2.. AI practices in the urban planning field

Practices	Usage
Urban Data Analytics and Planning Decision Support	AI transforms urban planning, optimising areas like traffic, air quality, and health, and traditional decisions like land use and master planning. AI's deep learning capabilities address citizens' concerns efficiently. It is a game-changer for traffic management, improving transportation networks in smart cities.
Urban and Infrastructure Management	AI, with machine learning, deep learning, and neural networks, aids in problem-solving, urban design, and infrastructure modelling. It enhances pedestrian satisfaction, land use, and transportation planning and supports public safety in smart city urban planning.
Urban Environmental and Disaster Management	Urban environmental and disaster management employs AI to address environmental issues and emergencies in cities, focusing on sustainability. It tackles various urban concerns, including tree management, noise pollution, population growth, and air pollution. AI, particularly machine learning, provides real-time analyses during crises and measures urban heat island effects in urban planning research.
Urban Monitoring and Development Control	AI monitors and manages urban growth and sprawl, predicts crime hotspots, identifies road improvements, assesses building configurations, simulates urban growth, and measures urban density and infrastructure impact, enhancing urban planning and development.

Source: Authors, extracted from Son et al. (2023)

Kamrowska-Załuska (2021) introduces an assessment framework to evaluate the impact of big data and AI tools on city design and planning. This framework considers factors such as the aim and range of data usage, types of AI tools, data sources, and their impact on urban design. The paper also classifies urban big data sources like sensor systems, user-generated content, administrative data, private-sector data, historical urban data, and hybrid data. The emergence of new data sources, including social media and governmental data, is highlighted as a significant development that enables precise geo-location and in-depth analyses of urban dynamics.

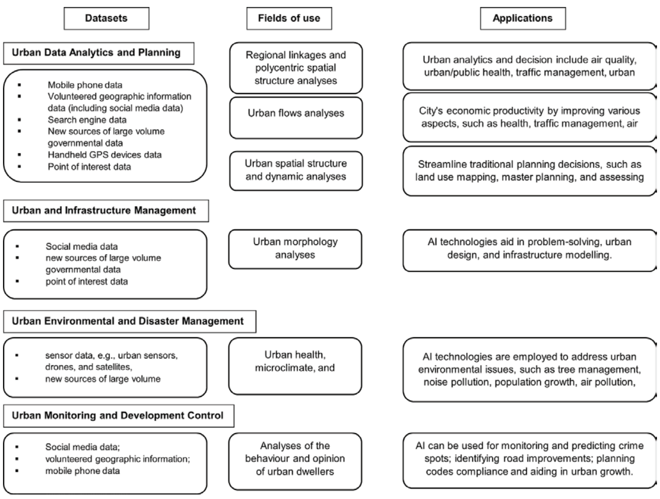

Figure 2. Datasets, fields of use, and AI applications in Urban Planning
Source: Analysis from Kamrowska-Załuska (2021) and Quan et al. (2019)

Moreover, Kamrowska-Załuska (2021) explores the types of AI-based tools used in urban planning, categorising them into four groups: artificial life, intelligent stochastic simulation models, evolutionary computing and spatial DNA, and knowledge-based intelligent systems. The integration of these AI tools is identified as an effective approach to address the limitations of individual tools in modelling urban growth and other urban phenomena.

The author also outlines the major fields of AI-based tools and big data applications in urban planning, encompassing regional linkages, urban spatial structure, urban flows, urban morphology, urban dwellers' behaviour and opinions, and urban health, microclimate, and environment. This typology offers insights into how AI-based tools and urban big data address various aspects of urban planning and development, highlighting their importance in the modern urban planning landscape.

In the context of urban planning, the utilisation of AI technologies presents both opportunities and limitations (Kamrowska-Załuska, 2021). One significant limitation is the potential for information bias, which can affect data from various sources. Information bias is a significant concern, affecting data from various sources. For example, volunteered geographic information, search engine data, and mobile phone data can have issues like duplicates and missing attributes. GPS data from floating cars might not provide a complete urban dynamics picture. Virtual world activities may not accurately represent real-life situations. Handling large-volume governmental data with various formats and social media data analysis can be challenging. Additionally, AI in urban planning may require costly equipment and maintenance, and diverse data access and governance conditions further complicate its use. Careful consideration of these limitations is essential for effective urban planning and development.

A Collaborative Future: Case Study from Global Cities

Exploring the global landscape of AI applications in contemporary urban planning, several cities have insightful cases, such as Australia, Cascais, Vienna, Calgary, and Hong Kong.

Each case presents innovative initiatives spanning Connected Automated Vehicles (CAV) technology, smart waste management, and real-time data integration, providing valuable perspectives on how AI contributes to overcoming urban challenges and optimising city operation.

Table 3. AI used in global cities

Countries/Cities	Key Highlights	Program & Status
Australia (Hajkowics et al., 2019; Yigitcanlar et al., 2020)	Australia is exploring CAV technology, AI for crowd movements, digital mapping of its built environment, and an AI-driven LIDAR system for 3D mapping, showing significant developments in AI applications for transportation, urban data, and infrastructure development.	Planned (roadmap), 2019
Cascais, Portugal (Antunes et al., 2021)	Cascais established the C2 command centre in 2018, optimising city operations and improving service quality through integrated data and processes, saving costs and enhancing efficiency. The platform includes various smart initiatives, resulting in substantial improvements, such as a smart waste management system reducing journeys by 180,000 km and saving EUR 600,000 annually while cutting carbon emissions by 350 tons.	C2, based on Deloitte OS, CitySynergy (Implemented)
Vienna, Austria (Antunes et al., 2021)	Vienna, an early adopter of open government data, greatly enhanced its capabilities with VeroCity, based on the European Commission's Context Broker. VeroCity provides real-time data for urban mobility, environmental monitoring, infrastructure, energy efficiency, and more, fostering transparency and citizen participation, introducing a chatbot that answers user questions and learns from interactions called WienBot.	VeroCity (Implemented)
Calgary, Canada (Antunes et al., 2021)	In 2015, Calgary expanded its *"Plant Information"* PI System to monitor its water source's watershed, collecting real-time data on water levels, flow rates, and rainfall. This system aids in predicting and addressing potential flooding, safeguarding water quality, and improving communication with the provincial government for coordinated flood responses.	Undefined system (Implemented)
Hong Kong (Antunes et al., 2021; Base, 2017;)	Hong Kong plans to deploy chatbots for efficient citizen responses. It uses real-time traffic data collected from sensors on major routes to reduce congestion. Additionally, various sensors monitor landslides, pollution, water levels, and energy data for disaster preparedness and city management.	Undefined system (Partly implemented)

Source: Antunes et al. (2021), Base (2017), Hajkowics et al. (2019), and Yigitcanlar et al. (2020)

Conclusion

Artificial Intelligence (AI) is reshaping urban planning by providing tools to optimise decision-making, predict trends, and simulate scenarios. This approach empowers planners to make data-driven decisions while underscoring the importance of public engagement and ethical considerations in the planning process. The potential of AI-driven urban planning is far-reaching, ranging from addressing traffic congestion and environmental sustainability to improving public service delivery.

As cities increasingly adopt AI in urban planning, challenges emerge, particularly concerning comprehensive datasets and transparency availability. Cities that struggle to provide adequate data pose limitations, as AI relies on robust datasets to effectively process and compute recommendations.

In third-world countries' cities, where data accessibility and transparency may lag compared to their developed counterparts, this challenge became more apparent. Issues ranging from government transparency to pervasive censorship contribute to these limitations, emphasising the need for concerted efforts to address data-related challenges for AI's widespread and equitable utilisation in urban planning.

The Smart Design framework, as discussed in the article, exemplifies how AI and urban planning can collaborate effectively. It employs a dynamic and iterative structure, facilitating the co-evolution of design problems and solutions. Involving various participants and utilising advanced AI techniques improves the efficiency and effectiveness of urban design processes. In summary, AI reshapes urban planning by offering tools to optimise decision-making, predict trends, and simulate scenarios. Urban planning, with AI as its ally, has the potential to create more efficient, sustainable, and equitable cities for the future.

Disclaimer

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