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Artificial Intelligence in Urban Development: A Systematic Review of Applications, Challenges and the Role of Urban Science

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ABSTRACT

Background: Rapid global urbanization and escalating environmental and social pressures call for more sophisticated approaches to urban management. Artificial intelligence (AI) has become a cornerstone of the smart-city paradigm. Its integration into urban development, however, is often hindered by algorithmic opacity, data bias and fragmentation, and the lack of robust socio-ethical frameworks. **Methods:** Following the PRISMA guidelines, a systematic literature review was conducted of peer-reviewed studies published between 2015 and 2025 and indexed in Scopus, Web of Science, IEEE Xplore and Google Scholar. Of 387 records identified, 58 duplicates were removed, 329 were screened, 156 were assessed in full text and 112 met the inclusion criteria. The included studies were synthesized thematically by AI technology, urban application domain and reported challenges. **Results:** The literature covers machine learning, deep learning, computer vision and, increasingly, generative models (generative adversarial networks, diffusion models and large language models). Five application domains dominate: intelligent transportation, environmental monitoring and sustainability, urban planning and design, public health and social services, and governance and citizen engagement. Six cross-cutting challenges recur: data quality and availability, algorithmic bias, explainability and trust, ethical and legal accountability, skills gaps, and the digital divide. Without deliberate countermeasures, these challenges can reproduce or deepen existing urban inequalities. **Conclusions:** AI should converge with the "New Urban Science", which grounds computational algorithms in human dynamics and in the theory of cities as complex adaptive systems. Realizing sustainable, equitable and resilient cities requires transparent and interoperable open-data infrastructures, explainable AI, algorithmic auditing, interdisciplinary capacity building, and inclusive participatory tools such as AI-enabled urban digital twins. These measures can ensure that technological innovation serves the public good.

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1. INTRODUCTION

The twenty-first century has seen unprecedented urbanization. The United Nations projects that 68% of the world's population will live in urban areas by 2050 [1]. This demographic shift, coupled with climate change, environmental degradation, resource scarcity and social inequality, places immense pressure on cities [2]. Cities must manage growing populations while ensuring sustainability, resilience and quality of life for their inhabitants.

In response, the concept of the "smart city" has gained considerable momentum. It envisions urban environments that use digital technologies to enhance efficiency, sustainability and well-being [3, 4]. Central to this paradigm is artificial intelligence (AI): technologies that enable machines to perform tasks requiring human-like intelligence, including learning, reasoning and decision-making [5]. AI has emerged as a critical enabler of sustainable and intelligent urban futures, offering opportunities to optimize urban systems, anticipate future trends and improve residents' quality of life [6, 7].

The use of computational intelligence in cities is not new. Recent advances in machine learning, deep learning and generative AI have, however, greatly expanded its range of applications [8]. From intelligent transportation systems and energy-efficient buildings to predictive analytics and environmental monitoring, AI is increasingly embedded in the fabric of modern cities [9, 10]. Generative models, such as large language models (LLMs) and generative adversarial networks (GANs), are opening new possibilities for urban design, scenario simulation and participatory planning [11, 12].

Despite this promise, the application of AI in cities is fraught with challenges. Data availability, algorithmic bias, transparency and ethical governance pose significant barriers to responsible deployment [3, 13]. The "black-box" nature of many models limits their interpretability, undermines public trust and raises questions of accountability and fairness [14, 15]. Existing reviews have tended to focus either on technical applications [4, 16] or on ethics and governance [13, 17]. Few have integrated the recent wave of generative AI with an explicit theoretical account of how urban science can shape responsible AI. This review aims to fill that gap by addressing four research questions:

RQ1. What are the key applications of AI in urban planning and development?

RQ2. What are the primary challenges and limitations of integrating AI into cities?

RQ3. How can urban science contribute to the responsible and ethical development of AI?

RQ4. What is the future trajectory of AI in shaping sustainable and equitable cities?

Section 2 describes the review methodology. Section 3 presents the theoretical background. Sections 4–7 report the findings on applications, challenges, the role of urban science and future directions. Section 8 discusses the findings and limitations, and Section 9 concludes with recommendations.

2. METHODOLOGY

The review followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA 2020) guidelines to ensure rigor, transparency and reproducibility [18].

2.1. Search strategy

Scopus, Web of Science, IEEE Xplore and Google Scholar were searched with keywords related to AI and urban development, combined with Boolean operators:

("Artificial Intelligence" OR "AI" OR "Machine Learning" OR "Deep Learning" OR "Generative AI" OR "LLM") AND ("Urban Development" OR "Urban Planning" OR "Smart City" OR "Urban Management" OR "Sustainable City")

The reference lists of key articles were also screened manually to identify relevant studies not captured by the database search. The final search was run on 31 December 2025. In Scopus, Web of Science and IEEE Xplore the string was applied to titles, abstracts and keywords; in Google Scholar, which returns results by relevance, the first 200 results were examined and the relevant ones retained. Because this is a single-author review, screening of titles,

abstracts and full texts, as well as data extraction, was carried out by one reviewer. Records were assessed against the eligibility criteria below, and the criteria were applied in the order listed.

2.2. Eligibility criteria

Studies were **included** if they (i) were published in peer-reviewed journals or conference proceedings; (ii) were written in English; (iii) focused on the application of AI technologies in urban contexts; (iv) provided empirical findings, theoretical insights or systematic reviews; and (v) were published between 2015 and 2025, including online-first versions, to capture recent advances. Studies were **excluded** if they did not directly address AI applications in urban settings, focused solely on general AI technology without urban relevance, or were opinion pieces, editorials or non-academic publications.

2.3. Study selection

The search identified 387 records (Figure 1): 367 from the databases (Scopus 142, Web of Science 108, IEEE Xplore 71, Google Scholar 46) and 20 from reference lists. After 58 duplicates were removed, 329 records were screened on title and abstract, 173 were excluded, and 156 articles were retrieved for full-text review. Of these, 44 were excluded: 19 had no direct urban application of AI, 9 dealt with general AI technology without urban relevance, 11 were opinion pieces, editorials or not peer-reviewed research, and 5 fell outside the 2015–2025 window. The remaining 112 studies were included. The review protocol was not registered in advance.

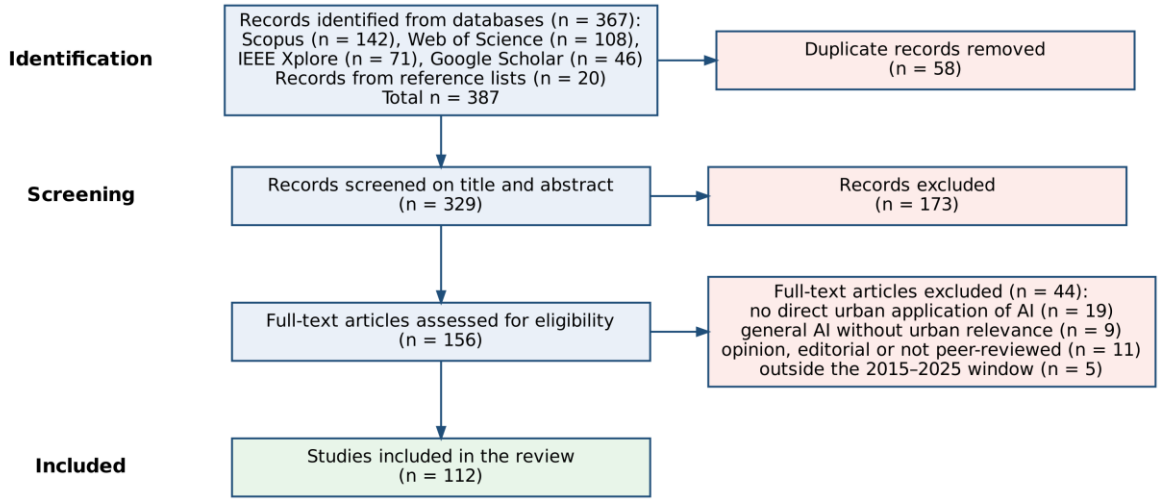


Fig. 1. PRISMA flow diagram of study selection.

2.4. Data extraction and synthesis

For each included study, the following data were extracted: author(s), publication year, AI technology, urban application domain, methodological approach, key findings and reported challenges. The extracted data were synthesized thematically. Studies were first coded by technology and domain, and the codes were then grouped into recurring patterns, trends and gaps that address RQ1–RQ4. The studies cited in this article, which illustrate each theme of the synthesis, are classified by domain, period and type in Table 1.

Table 1. Studies cited in this review, by thematic domain and publication year.

Thematic domain	Studies cited	*n*
Intelligent transportation	[19–21]	3
Environment and sustainability	[2, 7, 10, 22]	4
Urban planning, design and digital twins	[8, 11, 12, 23–25]	6
Public health and social services	[26, 27]	2
Governance, ethics and explainability	[3, 13, 14, 17, 28, 29]	6
Cross-cutting reviews and urban-science frameworks	[4, 6, 9, 15, 16, 30–33]	9
Total		**30**

Note. Methodological, foundational and regulatory sources (for example PRISMA, textbooks and legislation) are not included in the table. The complete list of the 112 included studies, with the extracted data, is available from the author on request.

The cited studies are concentrated in the most recent period: 21 of the 30 were published in 2022 or later, and 9 in 2025–2026 (including online-first versions). This reflects the rapid growth of research on generative and language-based AI in urban contexts.

3. THEORETICAL BACKGROUND

3.1. Defining artificial intelligence

AI is broadly defined as the capacity of machines to perform tasks that normally require human intelligence, such as learning, reasoning, perception and problem solving [5]. It encompasses machine learning (ML), deep learning (DL), natural language processing (NLP), computer vision and robotics. More recently, generative AI, including LLMs, GANs [34] and diffusion models, has emerged as a transformative force that can create new data, content and design alternatives [8]. Table 2 summarizes the main AI technologies identified in the reviewed literature and their urban applications.

Table 2. Key AI technologies and their applications in urban development.

AI technology	Key urban applications	Representative studies
Machine learning	Traffic prediction, energy optimization, demand forecasting, risk prediction	[21, 27]
Deep learning	Green-space mapping, air-quality prediction, image and video analysis	[12, 22]
Generative AI (GANs, diffusion models)	Urban design, scenario simulation, synthetic data, digital twins	[8, 11]
Large language models	Citizen engagement, policy analysis, mobility services, administrative automation	[20, 25]
Explainable AI (XAI)	Transparency, trust building, accountability in decision-making	[14, 15]
Computer vision	Traffic monitoring, infrastructure inspection, surveillance	[9, 10]

3.2. The smart-city paradigm

A smart city uses digital technologies to enhance efficiency, sustainability and quality of life [3]. Smart cities integrate information and communication technology (ICT), the Internet of Things (IoT) and AI across transport, energy, governance and public services [31]. Following the widely used framework of Giffinger et al. [35], six dimensions are commonly distinguished: smart economy (innovation-driven activities, digital entrepreneurship and data-driven business models), smart mobility (intelligent transport, traffic optimization and sustainable transit), smart environment (ecological monitoring, resource conservation and climate resilience), smart governance (e-government, participatory planning and transparent decision-making), smart living (technology-enabled health, education and leisure services) and smart people (digital literacy, civic engagement and inclusive participation) [6].

3.3. Urban science and the New Urban Science

Urban science is a multidisciplinary field that seeks to explain, discover, understand and generalize the complex dynamics of cities [15, 36]. It integrates geography, sociology, economics, planning and environmental science to analyze urban systems. The *New Urban Science* represents the convergence of urban science with advanced computational technologies, including AI, big-data analytics and urban digital twins [33]. This paradigm calls for data-driven, interdisciplinary and transdisciplinary approaches to understanding and managing urban complexity. It also warns against a purely technocratic “real-time city” in which data replace deliberation [37].

4. APPLICATIONS OF AI IN URBAN DEVELOPMENT (RQ1)

4.1. Intelligent transportation systems

AI has transformed urban mobility through intelligent transportation systems that optimize traffic flow, reduce congestion and improve safety [21]. Machine-learning algorithms analyze real-time data from sensors, GPS devices and social media to predict traffic patterns and adjust signal timings dynamically. Generative models are increasingly used to synthesize realistic mobility data. Diffusion models constrained by road-network topology, for example, can generate realistic vehicle and human trajectories for simulation and for training data-hungry models where real data are scarce or privacy-sensitive [19]. LLMs enable natural-language interaction with mobility systems, supporting multimodal journey planning and user-centric services [20].

4.2. Environmental monitoring and sustainability

AI plays a pivotal role in environmental monitoring and urban sustainability [10]. Machine-learning models predict air quality, trace pollutant sources and assess urban heat islands, providing actionable information for public-health interventions [27]. Deep-learning architectures such as U-Net and GANs enable high-resolution mapping of urban green space and the optimization of green infrastructure [12, 22]. AI also optimizes energy use in buildings, supports smart-grid management and facilitates the integration of renewable energy [7].

4.3. Urban planning and design

Generative AI is transforming planning and design by enabling the rapid generation of alternative layouts, scenario simulation and participatory co-design [8, 11]. Constrained deep convolutional GANs, for example, can generate green-space designs that comply with regulations and perform well ecologically [12]. Urban digital twins, virtual replicas of cities, allow planners to simulate policies and interventions before implementation, improving decision-making and stakeholder engagement [23]. LLMs assist in analyzing policy documents, automating administrative tasks and processing citizen feedback [25].

4.4. Public health and social services

AI strengthens urban public health through disease surveillance, predictive analytics and personalized care [27]. Machine-learning models analyze epidemiological data to anticipate outbreaks and inform resource allocation, and generative AI supports telehealth, patient engagement and health communication [7]. In social services, AI-powered chatbots and virtual assistants facilitate interaction between citizens and government, streamline service delivery and improve access to information [26].

4.5. Governance and citizen engagement

AI is reshaping urban governance by enabling data-driven decision-making, greater transparency and broader participation [3]. E-government platforms use NLP to analyze citizen feedback from social media and public consultations, predictive analytics support risk assessment and disaster management, and explainable AI can build trust and accountability [14]. Generative AI enables communities to visualize alternative urban futures and to co-design their cities [11, 24].

5. CHALLENGES AND LIMITATIONS (RQ2)

The integration of AI into urban development is accompanied by significant challenges that must be addressed to ensure equitable, sustainable and trustworthy outcomes. Table 3 summarizes these challenges and the mitigation strategies proposed in the literature.

Table 3. Challenges and mitigation strategies for AI in urban contexts.

Challenge	Description	Mitigation strategies
Data quality and availability	Fragmented, incomplete, siloed or biased data; privacy constraints	Open-data platforms; data-governance frameworks; synthetic data generation
Algorithmic bias	Discriminatory outcomes from biased training data or flawed algorithms	Fairness-aware design; continuous auditing; diverse and representative datasets

Explainability and trust	Opaque ("black-box") models limit understanding and public trust	Explainable AI techniques; preference for interpretable models in high-stakes decisions
Ethical and legal frameworks	Privacy, surveillance, liability and accountability concerns	Context-specific guidelines; regulation (e.g., the EU AI Act); stakeholder engagement
Skills gap	Limited AI literacy among planners, policymakers and administrators	AI and data-science training in planning curricula; interdisciplinary collaboration
Digital divide	Unequal access to technology and data across socio-economic groups	Equitable digital infrastructure; inclusive design of AI solutions

5.1. Data quality and availability

The effectiveness of urban AI depends on high-quality, representative and accessible data [16]. Urban data, however, are often fragmented, incomplete, siloed across institutions and subject to privacy regulations. Sensor networks may over-represent affluent neighborhoods, so that the digital divide is reproduced in the data themselves and leads to biased and inequitable outcomes [3]. Addressing these problems requires investment in data infrastructure, standardization and governance, and the careful use of synthetic data to augment sparse datasets [8].

5.2. Algorithmic bias and fairness

Algorithmic bias occurs when AI systems produce systematically prejudiced outcomes because of biased training data or flawed model design [13]. In cities, biased AI can lead to discriminatory policing, unequal access to services and the reinforcement of socio-economic inequalities. Mitigation requires careful dataset curation, fairness-aware algorithms and continuous auditing to detect and correct discriminatory patterns.

5.3. Explainability and trust

The opacity of many AI models, particularly deep-learning models, limits interpretability and undermines public trust [14]. Planners and policymakers need to understand not only what a model predicts but why, in order to design effective interventions. Post-hoc explanation techniques such as SHAP [38] and LIME [39] offer partial solutions. Further research is needed on transparent and accountable systems that non-experts can understand [15].

5.4. Ethical and legal frameworks

The deployment of AI in cities raises complex questions of privacy, surveillance, liability and accountability [3]. The European Union's AI Act [40] and similar frameworks address these concerns, including for generative AI [28]. Context-specific guidelines that reflect local values and priorities are still needed. Multi-stakeholder engagement, including community participation, is essential to align AI systems with societal expectations and human rights.

6. THE ROLE OF URBAN SCIENCE IN SHAPING AI (RQ3)

6.1. Embedding human dynamics

Urban science offers deep insight into human behavior, social networks and socio-spatial dynamics, all of which are essential for human-centric AI [30]. Incorporating these insights allows AI models to produce more accurate and socially meaningful predictions in public health, mobility and social services [15]. It requires a shift from techno-centric to human-centric frameworks that place people at the center of urban intelligence systems.

6.2. Promoting responsible AI development

Urban scientists are well placed to guide the ethical deployment of AI in cities by addressing data bias, privacy and fairness, so that AI benefits all residents. This means embedding transparency, accountability and inclusivity in the design and operation of AI-driven urban systems [17]. By fostering public participation and aligning AI with human values, urban science acts as a counterweight to purely techno-centric approaches.

6.3. Contextualizing AI in complex urban systems

Cities are complex adaptive systems with many interconnected components and non-linear interactions [36]. Urban science provides the theory and methods to understand these interactions, enabling AI to model and manage urban complexity more effectively [32]. Concepts such as path dependency, spatial autocorrelation and emergent

behavior are crucial for accurate urban modeling. A systems perspective is needed to avoid reductionist AI solutions that optimize one dimension at the expense of others, for example traffic throughput at the expense of air quality or equity.

7. FUTURE DIRECTIONS (RQ4)

7.1. Generative AI for urban design

Generative AI holds considerable potential for urban design and planning. Future research should develop hybrid models that integrate several generative techniques and multimodal data to produce coherent, sustainable and regulation-compliant designs [8, 12]. It should also examine how generative tools can support participatory planning by enabling communities to visualize and co-create urban futures.

7.2. Urban digital twins and AI integration

Urban digital twins are a promising platform for collaboration between AI and urban science [23]. By integrating real-time data, AI analytics and stakeholder input, they can support dynamic and participatory planning. Future work should prioritize co-design processes in which AI developers, planners and communities define and refine these models together, so that they reflect diverse perspectives and needs.

7.3. Explainable and responsible AI

Explainable and responsible AI is essential for trust and equity in urban applications. Research should advance transparent algorithms, fairness-aware modeling and governance frameworks that prioritize the public good and accountability [29]. This includes metrics and benchmarks for evaluating urban AI systems for bias, fairness and interpretability.

7.4. Bridging the digital divide

For AI to benefit all residents, the digital divide must be bridged. This requires investment in digital infrastructure in underserved communities, the promotion of digital literacy, and inclusive AI solutions that are accessible to diverse populations. Participatory design that involves marginalized communities in developing AI systems is essential for equitable outcomes.

8. DISCUSSION

8.1. Synthesis of findings

Across the reviewed literature, three patterns stand out. First, the technological frontier has shifted from predictive machine learning toward generative and language-based AI. Earlier studies concentrated on prediction and optimization in single domains such as traffic and energy [4, 9]. More recent work uses GANs, diffusion models and LLMs to *generate* design alternatives, synthetic data and conversational interfaces [8, 11, 25]. This shift moves AI from an analytical tool to a participant in design and deliberation, which raises new questions of authorship, validation and accountability.

Second, the challenges are cross-cutting rather than domain-specific. Data fragmentation, bias, opacity and the digital divide recur in every application domain. These problems are rooted in institutional arrangements, data infrastructures and power relations rather than in particular algorithms [3, 37]. Technical fixes such as XAI or fairness-aware learning are therefore necessary but not sufficient. They must be accompanied by governance reforms such as data stewardship, algorithmic auditing and regulation [13, 17].

Third, the literature increasingly converges on human-centred and systems-oriented framings. The New Urban Science [15, 33] and human-centred digital twins [23] both stress that urban AI must be grounded in an understanding of cities as complex social systems [36] and in participatory processes [24]. This convergence is the main theoretical contribution of this review. Urban science is not merely a field of application for AI; it supplies the theory, contextual knowledge and normative commitments that make urban AI valid and legitimate.

8.2. Implications

For research, the findings point to a shift from accuracy-centered evaluation toward assessment of fairness, interpretability, robustness and social impact. They also call for longitudinal studies of deployed systems rather than proof-of-concept prototypes. *For practice*, municipalities should treat data infrastructure and AI governance as public infrastructure. They should require explanation and audit for high-stakes systems, and they should use generative tools and digital twins to broaden participation rather than to replace deliberation.

8.3. Limitations of this review

This review has several limitations. (1) It included only English-language publications, which may under-represent research from non-English-speaking regions, including the Global South. (2) Google Scholar searches are less reproducible than searches of curated databases. (3) The inclusion window ends in 2025, so the most recent generative-AI applications are only partly covered. (4) Because the included studies were heterogeneous in design and outcome, a narrative thematic synthesis was used rather than a meta-analysis, and no formal quality-appraisal tool was applied. (5) Screening and extraction by a single reviewer increase the risk of selection error; dual independent screening is recommended for future updates. (6) The keyword string did not include terms such as “computer vision” or “digital twin”, which may have missed relevant studies.

9. CONCLUSION AND RECOMMENDATIONS

This review shows that AI is a transformative force in urban development, with opportunities to enhance sustainability, efficiency and quality of life in transport, environment, planning, health and governance. Its integration, however, is constrained by data quality, algorithmic bias, explainability and ethical governance. The convergence of AI and urban science, the “New Urban Science”, offers a way forward: AI’s technical capabilities combined with urban science’s understanding of social and spatial complexity can help create smarter, more equitable and more sustainable cities. Six recommendations follow.

Invest in data infrastructure: Cities should develop standardized, open and interoperable urban data platforms, supported by governance frameworks that ensure privacy, transparency and equitable access, and should explore synthetic data where data are scarce.

Promote responsible AI development: Urban AI should prioritize transparency, fairness and accountability, adopt explainable AI and embed ethical guidelines in design. Algorithmic audits and bias detection should become standard practice.

Foster interdisciplinary collaboration: Formal and informal structures should bring data scientists, planners, policymakers and communities together to co-design and co-implement AI solutions.

Bridge the skills gap: Universities and professional bodies should integrate AI and data literacy into planning and public-administration curricula and offer lifelong learning for practitioners.

Enable participatory planning: Generative tools and digital twins should be used to deepen public participation in scenario planning and co-design, and they should be accessible to all communities.

Develop ethical and legal frameworks: Context-specific guidelines and regulations should address privacy, liability and accountability. They should be developed through multi-stakeholder engagement and reflect local values and priorities.

Data availability

The search strings, the screening log and the list of included studies with the extracted data are available from the author on request.

Registration

The review protocol was not registered.

Conflict of interest

The author declares no conflict of interest.

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Use of AI tools

An AI-based tool was used to improve the language of the manuscript; the author reviewed the text and takes full responsibility for it.

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