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Smarter and healthier cities in the era of AI: A state-of-the-art review☆

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ABSTRACT

The smart city agenda has focused on technological solutions to urban problems. However, rapid social, environmental, and technological change, especially the rise of AI, have revealed significant transformations, highlighting the need for a state-of-the-art academic concept. This study proposes the concept of the *Smarter and Healthier city*, grounded in a systematic review of smart and healthy city research using the PRISMA protocol. We analyse the literature across three domains (governance, environment, and modelling) with emphasis on AI. In this study, we define smarter and healthier cities as AI-enabled urban systems that integrate advanced digital technologies with human-centred objectives, including environmental sustainability, and inclusive governance. Our review identifies that AI is driving conceptual transformations within the governance domain toward (1) integrative, (2) participatory, and (3) anticipatory governance, and within the environmental domain toward (1) dense IoT and crowdsensing infrastructures, (2) multimodal and transferable learning approaches, and (3) edge intelligence architectures. We further propose principles to address the emerging urban challenges, emphasising (1) ethical safeguards, (2) environmental justice, and (3) trustworthy AI systems. Overall, the smarter and healthier cities framework contributes an integrative perspective that bridges technological innovation, responsible governance, and human well-being in the context of AI-driven urban transformations and challenges.

1. Introduction

Since its emergence in the 1990s, the smart city agenda has largely centred on addressing urban problems through technological solutions (Kumar et al., 2022). However, societies worldwide have undergone profound social, environmental, and technological transformations, such as smartphones and COVID-19 pandemic. These transitions have reshaped smart city frameworks, underscoring the need to develop updated academic concepts that can address rapidly evolving demands for sustainable urban governance and environments. Among these transformations, the advancement of Artificial Intelligence (AI) stands out as one of the most impactful developments of the modern era. AI has emerged as a powerful tool capable of addressing a broad range of urban challenges by facilitating idea generation, optimise workflows, and supporting creative problem-solving, thereby enhancing collaborative urban planning and participatory governance processes (Agboola & Yassin, 2025). Yet despite its growing applicability, urban planners and decision-makers must critically assess how AI should be deployed to genuinely improve urban life. As AI-driven urban solutions reach a more mature stage, an urgent need arises to evaluate not only how AI can support the smart city agenda, but how it should be responsibly and effectively integrated into urban systems.

The Healthy Cities framework, promoted by the World Health Organization (WHO) (WHO, n.d.), emphasises the improvement of physical and social environments through the concept of health. By leveraging digital infrastructures such as IoT devices and sensor networks developed within smart city initiatives, Healthy Cities can contribute to reducing harmful environmental factors and enhancing urban health outcomes (Lifelo et al., 2024). Furthermore, grounded in health protection and sustainable development, the Healthy Cities approach adopts a multi-sectoral perspective encompassing social, governmental, and economic dimensions, while encouraging active community participation (Kamel Boulos & Al-Shorbaji, 2014). This holistic understanding of health provides a valuable next step for the smart city agenda in the era of artificial intelligence. As AI fundamentally transforms the ways in which technologies are deployed, governed, and

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integrated into urban environments, it also reshapes the relationship between technological advancement and sustainable human well-being. In this context, the Healthy Cities framework offers a pathway for guiding increasingly AI-enabled cities toward more responsible, sustainable, and human-centred forms of urban development.

In this study, we define smarter and healthier cities as AI-enabled urban systems that integrate advanced digital technologies with human-centred objectives. The proposed concept aims to identify the emerging transformations and challenges facing the physical and social environments of cities that are becoming increasingly smarter by AI and provides a multi-sectoral perspective for addressing these challenges in a technological, sustainable, and responsible manner. By doing so, it captures the AI-driven transformations reshaping urban systems that extend beyond the conceptual scope of existing smart city and healthy city frameworks. To explore these transformations, this study conducts a systematic literature review of recent research on AI and smart cities and healthy cities, thereby providing a comprehensive understanding of emerging trends, challenges, and guiding principles in the development of smarter and healthier cities.

This study introduces the concept of the *smarter and healthier city*, with particular emphasis on the transformation of the governance, environmental, and technical landscape driven by AI. The study is guided by three research questions:

(1) What are the current research trends in smart city literature in the era of AI?
(2) How has state-of-the-art AI reshaped the scholarly focus of smart city research?
(3) What challenges arise from these transformations, and what principles can guide the development of smarter and healthier cities?

The structure of this study is as follows. Introduction section introduces the background, rationale, and scope of the review. Literature review section introduces the existing concepts of the smart city and healthy city, exploring their interrelationship and highlighting the increasing role of AI-driven solutions. Methodology section outlines the research methodology, based on a systematic literature review. Bibliometric overview section presents the bibliometric analysis of the selected literature. Key Thematic Analysis section provides a thematic analysis organised around three key domains of smarter and healthier cities: governance, environment, and modelling. Key Findings and Challenges section demonstrates the AI-driven transformation of the smarter and healthier city concept and discusses the associated challenges and future directions. Finally, Conclusion section concludes by emphasising the significance of smarter and healthier cities and the critical importance of the responsible use of AI in their development.

2. Literature review

The smart city concept has emerged as a multidimensional paradigm that mobilises advanced digital technologies to address the structural challenges of rapid urbanisation (Afinowi, 2025; Bokhari & Myeong, 2022; Dalwai et al., 2023; Lifelo et al., 2024; Solanki et al., 2023). While no single canonical definition prevails (Afinowi, 2025; Mastrogiovanni, 2025), the literature converges around several influential conceptual frameworks that position smart cities as digitally connected urban environments integrating intelligent systems through networked infrastructures to achieve long-term sustainability goals (Hämäläinen & Tyrvainen, 2018; Kumar et al., 2022). From a technical standpoint, smart cities are conceptualised as interconnected "systems of systems" characterised by multi-layered technological architectures and dynamic data flows, supported by core infrastructures such as Internet of Things (IoT)-enabled sensing networks, real-time data platforms, and big data analytics (Almulhim & Yigitcanlar, 2025; Bokhari & Myeong, 2022; Harnal et al., 2022; Javed et al., 2022; Li et al., 2020; Moorthy & Marochi, 2025; Yigitcanlar et al., 2020).

Recent literature indicates a normative shift in smart city discourse, moving beyond mere efficiency-driven automation to increasingly evaluate success based on contributions to human well-being and socio-environmental sustainability (Hammoumi et al., 2024; Kaginalkar et al., 2023; Li et al., 2020; Lifelo et al., 2024; Rai et al., 2019) — a transition that has positioned smart governance as a critical driver for leveraging urban technologies with environmental protection and social equity (Almulhim & Yigitcanlar, 2025; Rasoulzadeh Aghdam et al., 2025). This shift increasingly aligns with global sustainability agendas, particularly the United Nations Sustainable Development Goals (UN SDG 11) (Almulhim & Yigitcanlar, 2025; Joseph, 2025; Mhlanga, 2022; Moorthy & Marochi, 2025), where digital transformation and AI are thus reframed as enabling instruments for enhancing social resilience, inclusivity, and lived experience (Dalwai et al., 2023; Gallego-Álvarez et al., 2025; Harnal et al., 2022; Lifelo et al., 2024; Solanki et al., 2023). As AI-enabled systems become further embedded in everyday governance (Sanchez-Anguix et al., 2021), the need to interrogate the governance domain becomes particularly urgent. The central question shifts from operational optimisation to how digitally mediated governance can meaningfully promote physical, mental, and environmental health within equitable and inclusive urban systems.

In this vein, the Healthy City framework offers an appropriate trajectory for the evolution of smart cities, guiding them toward a more human-centred urban paradigm with a sustainable environment. As mentioned above, the *Healthy City* concept is normatively rooted in the World Health Organization (WHO). Healthy Cities framework, which defines urban health not as fixed clinical outcomes but as sustained improvements in physical and social environments (WHO, n.d.). Within the smart environment domain, the advanced technical foundations established by smart city infrastructures provide essential prerequisites for reducing environmental footprints and enhancing overall quality of life (Lifelo et al., 2024; Rathi & Gola, 2024). Allam et al. (2019) further argue that addressing the complex interdependencies between environmental conditions and human health through AI and big data is increasingly necessary to support positive urban health interventions. Accordingly, in the context of healthy cities, the sustainable environment domain becomes central to understanding how the existing smart city agenda is being transformed in the era of AI.

In the era of AI, emerging techniques now enable far more efficient and safer urban solutions than traditional methods. Supported by modern sensing and communication infrastructures, cities can process large-scale datasets in real time, providing the foundation for effective deployment of Deep Learning (DL) and AI models (Alam et al., 2024; Lee et al., 2021; Mishra et al., 2025). AI-driven approaches reduce human labour, operational costs, and exposure to hazardous environments, thereby enhancing both efficiency and safety (Chauhan et al., 2023; Parimala Devi et al., 2025). Their ability to model the nonlinearity and complexity of urban systems positions AI as a pivotal technology for dealing with multi-layered urban problems (Ghoneim & Manjunatha, 2017; Zhang et al., 2021). As AI increasingly influences urban governance and environmental management, it becomes essential to examine how these technological advances reshape smart city agendas and ensure their responsible deployment.

In order to prepare the next direction of smart city and healthy city concepts in the era of AI, we suggest the concept of smarter and healthier Cities. The rapid advancement of AI is fundamentally reshaping the technological, social, and environmental dimensions of urban development, challenging the assumptions underpinning both smart city and healthy city frameworks. Existing smart city approaches have largely focused on efficiency, automation, and digital optimisation, whereas healthy city frameworks emphasise public health, environmental sustainability, and social well-being. However, neither perspective fully captures the transformative implications of AI for urban governance, stakeholder relationships, and human well-being. Consequently, there is an increasing need for a conceptual framework that integrates technological innovation with health, sustainability, and responsible governance. We define smarter and healthier cities as AI-enabled urban systems that integrate advanced digital technologies with human-centred objectives, including public health, environmental sustainability, and inclusive governance. The concept of smarter and healthier cities represents a state-of-the-art framework that integrates the strengths of both smart city and healthy city paradigms while addressing the challenges and opportunities arising from AI-driven urban transformation.

3. Methodology

This study presents a systematic review of the smart city and healthier city literatures, with particular attention to the role of AI. The aim of this study is to develop an expanded concept of smarter and healthier cities that shifts from the traditional smart city paradigm, and to suggest future directions for this concept through the effective and responsible use of AI.

To do this, conducting a systematic literature review serves several purposes. First, it identifies existing academic discussions on smart cities and examines how these debates have incorporated notions of "health," including environment and sustainability. Second, given the rapid pace of technological advancement in AI, the review assesses the recent trend of AI adoption within smart city initiatives. Finally, the systematic review identifies a significant academic transformation for demonstrating the concept of smarter and healthier cities and for outlining its potential future trajectories.

In this systematic review, we employed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) protocol to ensure a thorough and transparent approach. This protocol involves defining eligibility criteria for study selection, developing a comprehensive literature search strategy, selecting relevant studies, extracting data, assessing the risk of bias, and synthesising and analysing the collected data (Son et al., 2023). The literature across all domains was screened with a high level of methodological rigour to support robust findings.

3.1. Literature query strategy

Fig. 1 depicts the literature selection process. A search for relevant publications was conducted using the ScienceDirect database. To capture essential concepts, we combined a range of keywords that reflect both established and emerging AI technologies. A Boolean search query was executed using the following terms: ("smart cities" AND "healthier" AND "machine learning") OR ("smart cities" AND "healthier" AND "artificial intelligence") OR ("smart cities" AND "healthier" AND "deep learning"). These terms were selected because AI is often used interchangeably with "machine learning" and "deep learning," despite their technical distinctions.

3.2. Timeframe of the review

The search was limited to a 10-year period for two reasons: (1) to explore recent academic trends and capture the emerging concept of smarter and healthier cities, and (2) to identify the AI-driven transformations reshaping urban systems and the associated challenges that cities are likely to face in the future. To achieve this, the review incorporated studies addressing contemporary AI technologies and related debates within the established smart city and healthy city literature. Using January 2026 as the reference point, the search included publications published between 2016 and 2026.

3.3. Selection of studies

Given the broad interpretations of the smart city concept, we strategically categorised the literature into three representative domains. The first domain is *governance*, which has become central as smart city practices shift from technical optimisation toward social well-being, inclusivity, and equitable urban systems. This makes governance a critical lens through which to examine the deployment and implications of AI. The second domain is *environment*, a core thematic area for understanding healthier urban systems, as environmental conditions are closely linked to public health and ecological resilience. The third domain is *modelling*, which is particularly relevant in the era of AI, offering insight into how advanced analytical and computational techniques are being employed to support smarter and healthier urban systems. Categorising the literature into these three domains enables a multidimensional exploration of complex urban systems and ensures balanced consideration of the diverse stakeholders, processes, and spatial layers that shape contemporary cities.

The initial search returned a total of 1554 documents, including book chapters, journal articles, and conference proceedings. We then screened the retrieved journal articles by title and subsequently by abstract. Drawing on the authors' domain expertise, additional relevant

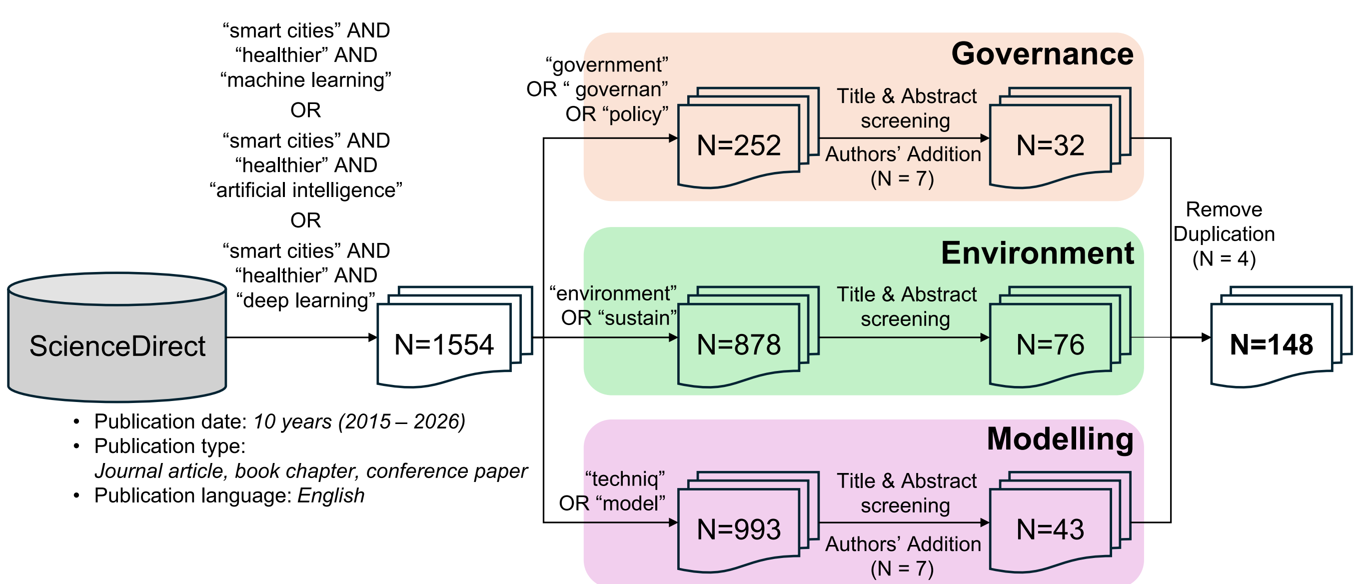

Fig. 1. Literature selection process.

studies were incorporated when they were deemed essential for addressing the research objectives. Throughout this process, studies that did not meet the eligibility criteria outlined in Table 1 were excluded. In addition, several journals deemed relevant by the authors were manually included to ensure comprehensive coverage of the research topic. Following this process, 32, 76, and 43 articles were retained for each domain, respectively, resulting in a final dataset of 148 articles included in the systematic literature review.

4. Bibliometric overview

4.1. Trend analysis

We conducted a trend analysis by publication year to examine the temporal research patterns and major agendas reflected in the selected articles. According to Fig. 2(a), two key findings emerge. First, the number of publications has shown a clear upward trend. Although two articles from 2014 were included through manual addition, the screening process revealed that only a small number of relevant studies were published prior to 2014. Since then, the volume of research has increased substantially and continues to rise. This rapid growth demonstrates that the academic discourse on AI-enabled smarter and healthier cities is expanding rapidly, underscoring the need for a systematic review to analyse emerging trends and thematic developments.

Second, based on the sharp increase in publications and the evolution of study keywords, the development of research themes can be categorised into three distinct periods: pre-2020 (Fig. 2(b), blue bars), 2020–2023 (Fig. 2(b), green bars), and post-2024 (Fig. 2(b), orange bars). Each bar graph presents the frequencies of keywords identified in the literature, listed in order of occurrence. To ensure analytical clarity, we excluded the primary search terms (smart city, smart cities, machine learning, deep learning, and AI). While interest in the IoT and big data remained consistently strong across all periods, notable temporal shifts in thematic focus are evident. Prior to 2020, most studies explored and proposed the potential application of AI in urban health systems using urban big data. From 2017 onwards, an increasing number of publications began to outline smart city frameworks and AI-enabled urban health services grounded in large-scale data analytics. Although the smart city concept predates this period (Kumar et al., 2022), publication activity increased notably after 2017. Advances in sensing and communication technologies that enable large-scale urban data processing further to support the rise of AI-driven urban health systems.

Between 2020 and 2023, research increasingly employed AI models to address real-world environmental challenges, particularly those related to sustainability, such as air quality and pollution forecasting. During this period, time-series forecasting DL architectures, including Long Short-Term Memory (LSTM), and Gated Recurrent Unit (GRU) models, were applied more extensively in studies focusing on urban environmental problems (Chauhan et al., 2023; Faydi et al., 2023). Additionally, COVID-19 has become an important scholarly keyword by linking with the healthcare sector. Several studies began leveraging AI technologies to analyse, monitor, or manage pandemic-related quarantines using the accumulated COVID-19 datasets (Alsalamah, 2023; Leelavathy & Nithya, 2021).

Table 1
Exclusion and inclusion criteria.

Inclusion criteria	Exclusion criteria
• Both relevant to smart city and healthy city • Within the domain of city, urban or regional studies • Related to sustainable urban development • Book chapter, journal article, or conference proceeding	• Soley focused on the development of machine learning (ML) or AI models • Within the domains of smart cities and healthier cities, but not addressed AI-related aspects • AI studies do not fall in the urban or regional studies • Irrelevant to the research aim

After 2024, the keyword “big data” largely disappeared from the literature, while air quality and pollution forecasting became central themes in environmental-sustainability research. Our database also indicates a notable increase in journal articles aimed at air quality prediction employing state-of-the-art AI techniques after 2024 (Alnowaiser et al., 2024; Binbusayyis et al., 2024; Dey, 2024; Naveed et al., 2025). In addition, generative AI (GenAI) became widely introduced during this period. Two years after the release of ChatGPT in late 2022, global awareness of GenAI's potential had intensified substantially, contributing to a marked expansion of academic interest in AI-enabled urban studies (Al-Enezi et al., 2025; Gallego-Álvarez et al., 2025; Năstasă et al., 2025). Beyond environmental forecasting and management, research has increasingly focused on the digital transformation of governance and administrative functions (Almulhim & Yigitcanlar, 2025; Joseph, 2025; Mastrogiovanni, 2025; Rasoulzadeh Aghdam et al., 2025). Moreover, environmental studies began to move beyond predictive modelling toward real-time monitoring and the integration of robotics with AI systems, signalling a shift toward more operational and physically embedded urban solutions (Alnowaiser, 2025; Maske et al., 2025; Naveed et al., 2025; Salian et al., 2025).

In summary, the number of studies in this field continues to increase, and the IoT and big data remain a consistently prominent topic in academic discourse, which enables the AI-driven technical urban solutions. However, despite the earlier origins of the smart city concept, major events (such as the COVID-19 pandemic) and significant advancements in AI, including time-series forecasting models like LSTM and GRU, as well as GenAI, have substantially influenced research trends. Time-series forecasting for air-quality prediction remains the most dominant theme, while GenAI has recently emerged as a key agenda-shaping urban planning and governance research.

4.2. Regional analysis

To examine the geographical distribution of the literature, the reviewed articles were classified according to the affiliation of the first author and subsequently analysed by country, continent, and Global North–South categories. As Fig. 3-(a) exhibits, the results reveal a strong geographical concentration of research in Asia. The top contributing countries were India (43 articles), China (17), Saudi Arabia (16), Spain (6), South Korea (6), Australia (5), Italy (5), Pakistan (4), the United States (4), and United Kingdom (4), followed by Morocco, and Iran (3 each).

At the continental level (Fig. 3-(b)), Asia accounted for the majority of publications (68.9%), followed by Europe (18.9%), North America (4.1%), Africa (4.1%), Oceania (3.4%), and South America (0.7%). Overall, the literature is heavily dominated by Asian countries, particularly India and China, reflecting the rapid urbanisation and growing adoption of AI-enabled urban technologies within the region.

A comparative analysis between developed and developing countries further reveals notable differences in research focus and objectives. Studies originating from developed regions, particularly Europe and North America, tend to emphasise institutional and governance-oriented perspectives. These studies frequently focus on themes such as governance, inclusiveness, policy development, participatory decision-making, and data governance frameworks. For example, European research has played a leading role in advancing sustainable cities through robust governance structures, participatory approaches, and regulatory frameworks that support responsible technology deployment (Almulhim & Yigitcanlar, 2025; Gallego-Álvarez et al., 2025; Mastrogiovanni, 2025).

In contrast, studies from developing countries, particularly India and China, are more likely to focus on the practical application of AI technologies to address challenges associated with rapid urbanisation. Common themes include the deployment of deep learning, machine learning, and AI-driven analytical models for environmental monitoring, resource management, and sustainable urban development (Fang

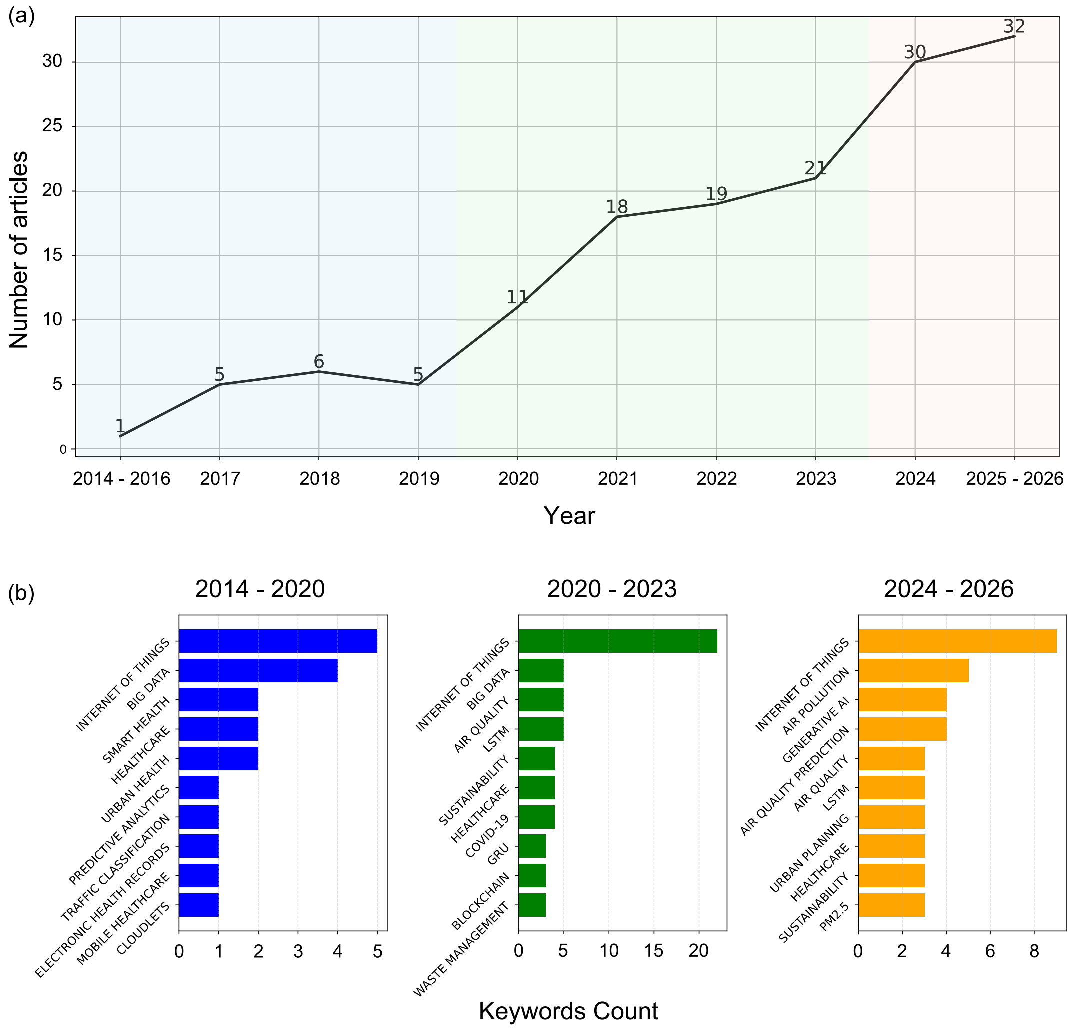

Fig. 2. Number of articles by year (a) and key themes (b).

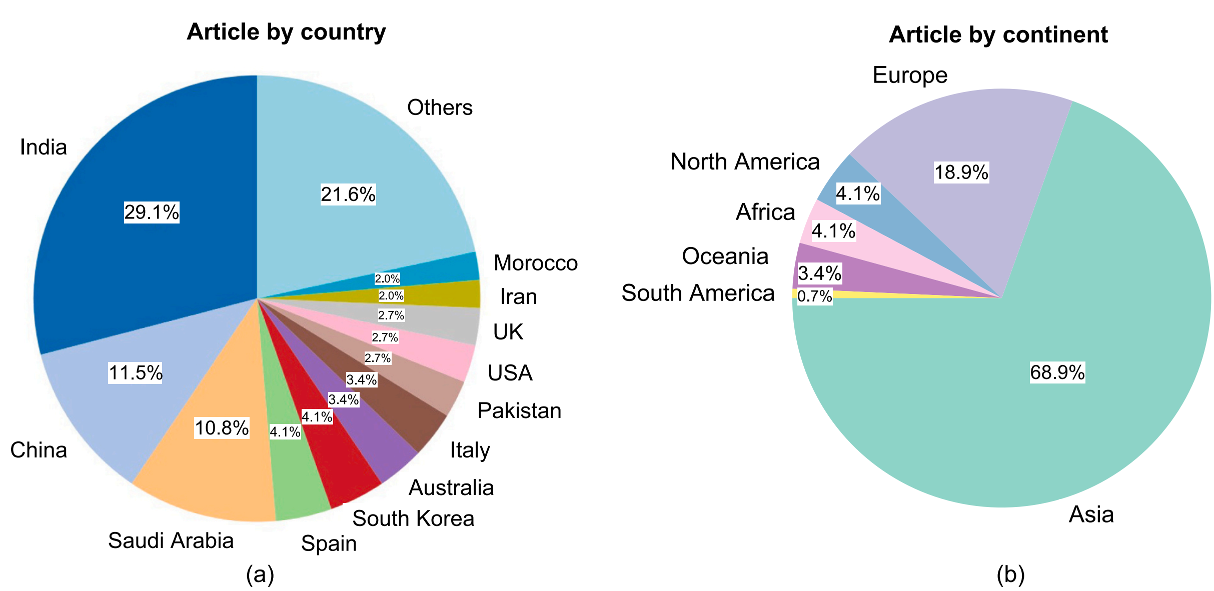

Fig. 3. Number of studies by country (a) and continent (b).

et al., 2023; Maske et al., 2025; Mehmood et al., 2025; Mengash, Alharbi, et al., 2022). This emphasis reflects the urgent need to address large-scale urban challenges through technological innovation.

The Global North–South comparison provides further insight into these differences. Agboola and Findikgil (2023) and Zakka et al. (2025) emphasised the importance of understanding the diverse contexts, challenges, and implications of smart city development across the Global North and Global South, drawing on case studies from Nigeria and other African cities. Cities in the Global North generally benefit from mature institutions, established regulatory frameworks, and well-developed urban infrastructures, enabling researchers to focus on governance mechanisms and responsible AI deployment. In contrast, cities in the Global South often face constraints related to institutional capacity, financial resources, and technological infrastructure, leading to greater attention being paid to implementation challenges, resource optimisation, and capacity building (Afinowi, 2025; Agboola & Findikgil, 2023; Zakka et al., 2025). These findings suggest that while AI-driven urban transformation is a global phenomenon, research priorities remain strongly influenced by regional socioeconomic and institutional contexts.

4.3. Keywords and subdomains

We conducted a keyword analysis to identify the major topics and subdomains represented in the selected studies. Fig. 4 provides a holistic overview of this landscape by visualising the frequency distribution of keywords extracted from the reviewed literature. At this broad level, three keywords appear most prominently, indicating the dominant thematic clusters within the field. The first is IoT, which had the highest occurrence (k = 36). IoT refers to networks of interconnected devices, vehicles, wearables, and sensors that autonomously collect and exchange data, enabling real-time monitoring and automated responses (Gong et al., 2023; Khan et al., 2023). Functioning as the technological backbone of smart city systems, IoT connects physical and digital infrastructures, allowing cities to optimise services, enhance sustainability, and improve residents' quality of life (Harnal et al., 2022; Khan et al., 2023). The second major keyword relates to air pollution, particularly air quality management. Frequent terms include *air pollution* (k = 9), *air quality* (k = 8), *air quality prediction* (k = 5), and *PM2.5* (k = 4). As air quality is a critical determinant of public health, coordinated monitoring and governance remain essential (Bekkar et al., 2021). The third major keyword concerns healthcare and smart health (k = 9 and k = 6). While traditional healthcare has been hospital centred (Cook et al., 2018), technological advances have led to smart health systems integrating biomedical sensing and intelligent computation to deliver proactive and personalised care (Abdeen et al., 2022).

From the perspective of the three domains, several keywords in Fig. 3 warrant more detailed attention. In the governance domain, terms such as *e-governance*, *participatory*, and *people-centric* appear prominently. These keywords indicate that many studies address governance related concerns, pointing to subdomains such as governance systems, citizen participation, and human-centred digital governance practices. In the environmental domain, frequently occurring terms—*air quality*, *pollution*, *waste management*, *water management*, and *sustainability*—suggest that environment focused studies use diverse approaches to examine how AI supports smart city and healthier city agendas. Likewise, highly technical modelling related terms such as *LSTM*, *CNN*, *multimodal learning*, and *generative AI* reflect the variety of advanced AI models developed or applied in the selected literature.

Given the breadth and heterogeneity of these keyword clusters, classifying the literature into clear subdomains is essential for systematically examining the distinct nature, priorities, and methodological tendencies within each domain. In the following sections, we elaborate on each domain and its associated subdomains as derived from these keyword patterns.

5. Key thematic analysis

5.1. Governance

The reviewed articles reveal several governance-related subdomains, each summarised with its corresponding key concepts and thematic focus (see Table 2). Digital governance, often referred to as e-governance or smart governance, constitutes the foundational infrastructure of smart cities, representing a strategic integration of digital technologies, data-driven decision-making, and participatory mechanisms (Almulhim & Yigitcanlar, 2025; Harnal et al., 2022; Rasoulzadeh Aghdam et al., 2025). As digitisation has exposed inefficiencies embedded in analogue administrative systems, digital governance has evolved from procedural bureaucratic digitalisation into a

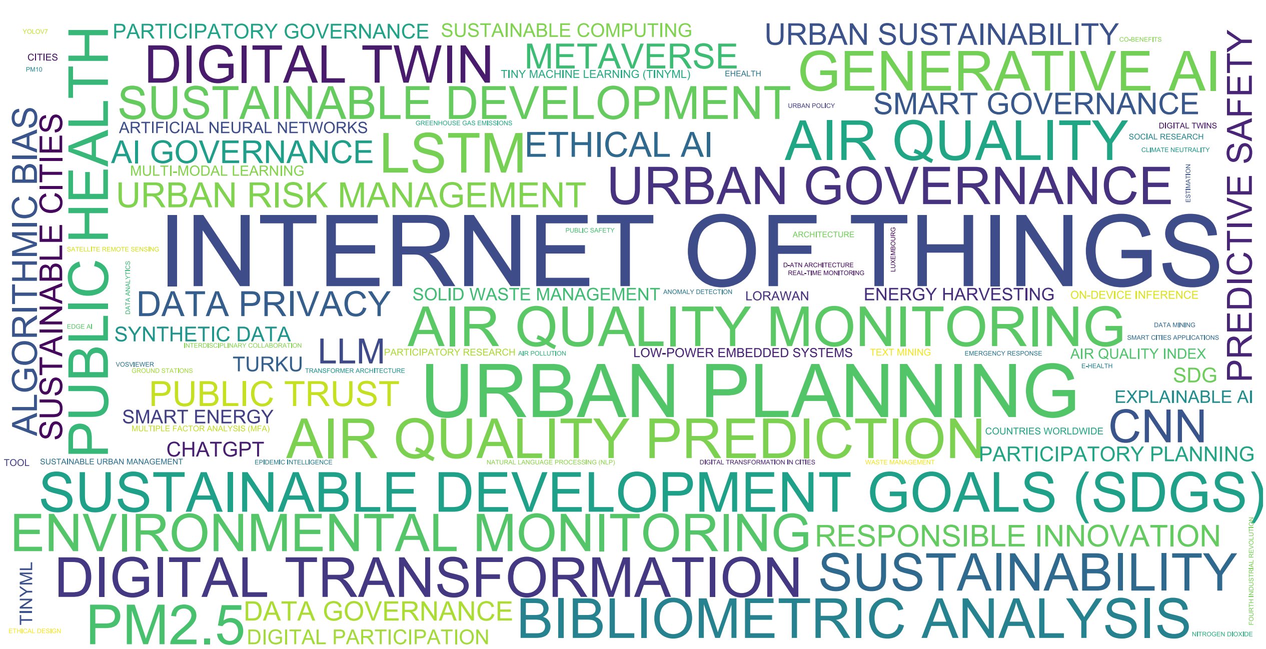

Fig. 4. Word cloud for the keywords.

Table 2
Key analysis in governance domain.

Subdomain	Key concepts	Contents	Articles
Integrative Smart City Governance Frameworks	Smart city governance models / Policy framework Urban governance structure /Digital governance	Emerging Research Trends: Recent scholarship shows exponential growth centred on the interplay between participatory governance, data security, AI, and sustainable development, with a specific focus on blockchain and IoT technologies.	Rasoulzadeh Aghdam et al. (2025); Năstasă et al. (2025); Almulhim and Yigitcanlar (2025)
		Role and Elements of Governance: Smart governance is a key driver for sustainable urban development, and its effectiveness is determined by digital infrastructure, data management, citizen participation, and institutional capacity.	Almulhim and Yigitcanlar (2025); Rasoulzadeh Aghdam et al. (2025); Afinowi (2025)
		Integrated Technology Utilisation: Digital management approaches that integrate innovative technologies like IoT, machine learning (ML), and drones provide new pathways for sustainability throughout the entire urban lifecycle, from planning to maintenance.	Afinowi (2025); Naveed et al. (2025); Albadrani (2025)
		AI-Driven SDG Alignment: AI contributes to achieving SDGs by enabling data-driven environmental and urban policy solutions	Gallego-Álvarez et al. (2025); Joseph (2025)
		AI-Driven Governance for Sustainable Development: Artificial intelligence serves as a critical enabler for sustainable development by optimising resource use and enhancing data-driven decision-making across urban development and healthcare, though its successful governance requires addressing significant technological, ethical, and regulatory barriers.	Joseph (2025); Lifelo et al. (2024); Bosco et al. (2026)
		Framework for Technological and Social Integration: A city's smart status is fundamentally driven by technological integration, which must be combined with smart applications that enhance civic engagement and mobility to create sustainable urban spaces, all guided by a robust framework of consistent key indicators.	Hammoumi et al. (2024)
		AI-Enabled Framework for Sustainable Development: AI accelerates progress toward SDGs by enabling efficient governance and environmental monitoring.	Solanki et al. (2023); Joseph (2025); Gallego-Álvarez et al. (2025)
		Holistic Framework for AI Integration: AI research in smart cities is rapidly expanding across urban governance and infrastructure, emphasising that while AI is a transformative force, its successful implementation requires a systematic approach that addresses the specific potentials, conditions, and obstacles of each region.	Harnal et al. (2022); Almulhim and Yigitcanlar (2025); Afinowi (2025)
		Strategic Evolution for Global Sustainability: The transition to smart cities represents an essential and inevitable evolution of urban planning, where the integration of technological innovation with environmental and social governance strategies is fundamental to achieving global sustainability goals.	Javed et al. (2022); Al-Enezi et al. (2025)
		Integrated System of Systems Architecture: Future smart cities	Kumar et al. (2022); Javed et al. (2022);

(continued on next page)

Table 2 (*continued*)

Subdomain	Key concepts	Contents	Articles
		are conceptualised as an integrated 'system of systems' rather than isolated entities, requiring a next-generation standard architecture that incorporates 6G, Industry 5.0, disaster recovery, and human well-being to address urban challenges and enhance long-term sustainability.	Almulhim and Yigitcanlar (2025)
		Necessity of Systematic Models: To efficiently coordinate complex urban ecosystems, the 'Smart City Concept Model (SCCM)', which integrates strategy, technology, governance, and stakeholders, should be utilised as a systematic operational tool.	Hämäläinen and Tyrvainen (2018); Javed et al. (2022)
Citizen Participation & Social Governance	Participatory governance / Citizen participation / Social media / Stakeholder engagement	Strengthening Participation through Two-way Communication: To ensure public safety and compliance during crises, governments must shift from one-way information broadcasting to a two-way networking strategy that fosters active citizen engagement and trust.	Dalwai et al. (2023); Almulhim and Yigitcanlar (2025)
		Building a Collaborative Data Ecosystem: To break down institutional silos and improve decision-making, an accessible urban data governance ecosystem must be established to enable seamless data exchange and build trust among all stakeholders.	Kaginalkar et al. (2023); Bokhari and Myeong (2022); Mastrogiovanni (2025)
		Integrating Social Science Insights: To manage the risks and opportunities of the digital revolution, social science analysis must be integrated into policymaking to evaluate the ethical and social impacts of technology on citizens' lives.	Hantrais and Lenihan (2021); Rasoulzadeh Aghdam et al. (2025); Bokhari and Myeong (2022)
		Integration of Social and Intelligent Applications: Future cities must leverage the synergy between artificial intelligence and social applications to encourage citizen participation in the urban digital ecosystem, effectively tackling complex urban challenges	Sanchez-Anguix et al. (2021); Bokhari and Myeong (2022)
		Improving Responsiveness to Citizen Needs: By utilising technologies like Natural Language Processing (NLP) to analyse public sentiment, governance systems can become more responsive and better aligned with the actual needs of the community.	Leelavathy and Nithya (2021); Jauhiainen et al. (2026); Liu et al. (2020)
		Evaluating Value through 'Smart Society' Metrics: The success of a smart city should be measured by the quality of 'Smart Society' implementation, such as online service capability and data openness, rather than just technical infrastructure.	Li et al. (2020); Almulhim and Yigitcanlar (2025)
		Establishing Human-Centred Urban Identity: Beyond economic efficiency, smart cities must place culture and spiritual values at the core of urban design to ensure emotional well-being and sustainable happiness for all residents.	Rai et al. (2019); Alves et al. (2024)
AI-driven Data Governance & Public Decision-making	AI-based policy decisions / Administrative services / Data-driven decision-making	Crisis Management & Resilience: AI-based decision-support and early warning systems enhance urban resilience by utilising predictive analytics to enable faster, data-driven responses to complex crises.	Al-Enezi et al. (2025); Jayachandran et al. (2025); Javed et al. (2022)
		Data-Driven Decision Support for SDGs: Big data optimises public	Moorthy and Marochi (2025); Joseph (2025)

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Table 2 (*continued*)

Subdomain	Key concepts	Contents	Articles
		decision-making in healthcare, urban planning, and environmental conservation, but requires robust governance to ensure ethical integrity and sustainable policy outcomes.	
		Social Innovation in Decision-Making: AI-driven decision-making acts as a form of social innovation that improves governance efficiency by sharing collected data with entrepreneurs and stakeholders to benefit society at large.	Bokhari and Myeong (2022); Mastrogiovanni (2025)
		Holistic Data Management: A comprehensive research framework is required to address the significant challenges and complexities posed by the diverse data streams generated by IoT and smart government AI applications.	Al-Besher and Kumar (2022); Chen et al. (2021); Javed et al. (2022)
		Collective Intelligence: The integration of AI with crowd-based data enhances public decision-making by incorporating the collective intelligence of citizens into formal governance systems.	Liu et al. (2020); Kaginalkar et al. (2023)
Ethical and Responsible AI Governance	Ethical AI / Data privacy / Trust / Responsible AI	Framework for Citizen-Centric AI Governance: To develop truly citizen-centric smart cities, AI research and policy must integrate multi-dimensional governance factors – including ethics, privacy, transparency, and participatory design – within a comprehensive framework that aligns technological innovation with social responsibility.	Năstasă et al. (2025); Mastrogiovanni (2025); Rasoulzadeh Aghdam et al. (2025)
		Ethical Frameworks & Inclusivity: The ethical challenges of urban digital transformation – namely privacy, equity, and transparency – necessitate the use of regulatory sandboxes and participatory governance to ensure cities remain inclusive and aligned with societal values.	Chen (2025)
		Balancing Efficiency and Trust: Responsible AI-driven governance must harmonise technological optimisation with legal safeguards and capacity-building to improve urban resilience while maintaining public trust and regulatory compliance.	Mastrogiovanni (2025); Almulhim and Yigitcanlar (2025); Afinowi (2025)
		Human-Centred Values: Beyond mere technological advancement, true smart cities must prioritise human-centred governance models that ethically integrate citizens' emotional and psychological needs into urban policy.	Alves et al. (2024); Chen (2025)
		AI-Enabled Metaverse for Urban Transformation: Emerging AI-powered metaverse platforms may reshape smart city governance by fostering stakeholder collaboration and enhancing urban adaptability, provided that advancing algorithms are balanced with robust privacy, security, and ethical AI practices.	Lifelo et al. (2024); Jauhiainen et al. (2026);
		AI-Driven Ethical Governance for Human-Centric Smart Cities: Integrating AI is essential for enhancing the efficiency and sustainability of smart city governance, necessitating the	Bosco et al. (2026); Mastrogiovanni (2025); Chen (2025)

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Table 2 (*continued*)

Subdomain	Key concepts	Contents	Articles
		application of a systematic analytical framework to measure and manage ethical principles throughout the entire project life cycle.	
		Implicit vs. Explicit Ethics: While city managers often prioritise legal regulations over formal ethical norms, their decision-making processes still contain inherent ethical content regarding transparency and citizen rights that must be acknowledged.	Ehwi et al. (2022)
		Human-Centred AI for Sustainability: Prioritising human-centred AI is essential for the ethical deployment of governance systems and the successful achievement of global sustainable development goals.	Mhlanga (2022); Bosco et al. (2026)
		Addressing the Research Gap in AI Risks: Despite the growing demand for AI-enabled urban innovation, there is a critical lack of scholarly research investigating the systemic risks and upcoming social disruptions of wider AI utilisation, highlighting the urgent need for responsible governance.	Yigitcanlar et al. (2020); Rasoulzadeh Aghdam et al. (2025); Chen (2025)

comprehensive governance framework that supports systemic transformation (Al-Besher & Kumar, 2022; Javed et al., 2022; Kumar et al., 2022).

Recent scholarship (Almulhim & Yigitcanlar, 2025; Rasoulzadeh Aghdam et al., 2025) conceptualises it as a strategic integration where our analysis of 32 core research papers identifies ‘Integrative Smart City Governance Frameworks’ as the most dominant subcategory. These frameworks establish that governance effectiveness depends on the strategic alignment of digital infrastructure, institutional capacity, participatory processes, and sound data governance (Almulhim & Yigitcanlar, 2025). Within this paradigm, a city's ‘smartness’ is not merely a technical status but a result of integrating digital management with institutional capacity to support the entire urban lifecycle (Afinowi, 2025; Javed et al., 2022). Consequently, smart city governance frameworks represent a systematic ‘system of systems’ architecture that integrates advanced technologies, such as AI, IoT, and 6G, with these institutional and participatory elements to drive sustainable urban development and align city operations with Global SDGs) (Gallego-Álvarez et al., 2025; Javed et al., 2022; Joseph, 2025; Kumar et al., 2022; Solanki et al., 2023).

This institutional evolution has been accompanied by a shift toward ‘Citizen Participation and Social Governance’, moving away from hierarchical, top-down governance models toward networked, multi-actor systems (Bosco et al., 2026; Hämäläinen & Tyrvainen, 2018). Effective AI-enabled digital governance requires interoperable data infrastructures, cross-sectoral information exchange, and multi-stakeholder collaboration that transcend siloed governmental structures (Kaginalkar et al., 2023; Yigitcanlar et al., 2020). In this context, citizens are increasingly conceptualised as co-creators of public value, with digital platforms and crowdsourcing mechanisms facilitating e-participation, collaborative policymaking, and risk communication (Almulhim & Yigitcanlar, 2025; Dalwai et al., 2023; Hämäläinen & Tyrvainen, 2018; Hammoumi et al., 2024). Ultimately, this necessitates a shift toward a human-centred, two-way collaborative ecosystem that integrates social science insights and intelligent applications, such as NLP-driven sentiment analysis, to enhance institutional responsiveness and measure success through ‘Smart Society’ metrics, including data openness and emotional well-being (Leelavathy & Nithya, 2021; Li et al., 2020; Rai et al., 2019). Beyond operational efficiency, AI contributes to surveillance enhancement, cybersecurity resilience, disaster management planning, and participatory innovation, enabling citizens to act as ‘citizen scientists’ within urban governance ecosystems (Yigitcanlar et al., 2020). Consequently, participatory governance, combined with investments in human and social capital, strengthens sustainable urban development and resource management (Li et al., 2020).

In parallel, digital governance is transforming into ‘AI-driven Data Governance and Public Decision-making’, shifting toward intelligent, data-centric, and anticipatory governance systems (Joseph, 2025; Li et al., 2020). Structured data governance frameworks now organise processes into functional components such as data classification, consent management, and value creation for public benefit (Mastrogiovanni, 2025). Within this framework, predictive analytics and early warning systems enhance urban resilience by transforming diverse IoT data streams into a form of social innovation that integrates collective intelligence into formal governance (Al-Besher & Kumar, 2022; Al-Enezi et al., 2025; Liu et al., 2020). Contemporary research highlights the integration of AI tools, such as predictive analytics, automated decision-support systems, and algorithm-assisted urban management, into policy processes to enhance optimisation, risk forecasting, and real-time coordination (Bokhari & Myeong, 2022; Hammoumi et al., 2024; Năstasă et al., 2025). This development signals a movement from reactive to proactive governance, enabling cities to anticipate and address complex challenges, including climate change, public health crises, demographic pressures, and resource scarcity (Joseph, 2025).

However, the expansion of these data-centric and anticipatory governance has intensified normative concerns regarding power, accountability, and democratic control, leading to a focus on ‘Ethical and Responsible AI’. Scholarly attention is shifting toward more inclusive and democratically grounded smart governance models that prioritise ethical, social, and environmental dimensions (Mastrogiovanni, 2025; Năstasă et al., 2025). To achieve this, some argue that establishing a comprehensive, human-centric AI governance framework is essential (Alves et al., 2024; Mhlanga, 2022; Năstasă et al., 2025). Such a framework must integrate multi-dimensional factors, including ethics, privacy, transparency, and participatory design, to ensure that technological innovation remains fundamentally aligned with social responsibility (Chen, 2025; Năstasă et al., 2025). Central to this evolution is the strategic balance between operational efficiency and public trust (Mastrogiovanni, 2025). By implementing practical oversight mechanisms such as regulatory sandboxes and legal safeguards, cities can maintain regulatory compliance while addressing systemic risks, even within emerging platforms like the AI-powered metaverse (Bosco et al., 2026; Chen, 2025; Lifelo et al., 2024; Mhlanga, 2022).

The literature reveals a notable tension between techno-optimistic and critical perspectives on AI-enabled urban governance. Techno-optimistic studies emphasise the potential of AI to enhance efficiency, sustainability, and SDG achievement through data-driven governance and decision-making (Solanki et al., 2023; Lifelo et al., 2024; Bosco et al., 2026; Joseph, 2025). In contrast, critical studies highlight concerns related to algorithmic opacity, governance complexity, democratic accountability, and the redistribution of decision-making power within increasingly automated urban systems (Ehwi et al., 2022; Yigitcanlar et al., 2020). Despite these differences, both perspectives converge on the importance of transparency, accountability, fairness, and participatory governance as essential principles for responsible AI deployment (Almulhim & Yigitcanlar, 2025; Mastrogiovanni, 2025). However, relatively few studies examine the long-term social, political, and experiential implications of AI-mediated governance, revealing a significant gap in understanding how AI reshapes democratic practice, civic engagement, and citizen well-being. This gap has further led to growing calls in the literature for more integrated and human-centred approaches to AI governance that extend beyond technical optimisation to include democratic legitimacy, social experience, and ethical responsibility (Alves et al., 2024; Chen, 2025; Rai et al., 2019).

Overall, the integration of AI marks a further stage in the evolution of digital governance. AI-driven digital governance is increasingly conceptualised as a multidimensional paradigm that seeks to balance efficiency, democratic innovation, sustainability, and social equity within complex urban ecosystems (Almulhim & Yigitcanlar, 2025; Gallego-Álvarez et al., 2025; Liu et al., 2020; Rasoulzadeh Aghdam et al., 2025). Importantly, this evolution extends digital governance beyond administrative optimisation toward broader societal outcomes, including public health resilience, environmental sustainability, and improved quality of life (Lifelo et al., 2024; Mhlanga, 2022). As cities confront intertwined challenges such as climate change, demographic pressures, resource scarcity, and health inequalities (Almulhim & Yigitcanlar, 2025; Kaginalkar et al., 2023; Lifelo et al., 2024), AI-enabled governance systems are increasingly positioned as critical infrastructures for promoting healthier and more sustainable urban environments (Moorthy & Marochi, 2025). This orientation toward health-centred and sustainability-driven urban governance forms the basis for examining how AI-enabled digital systems contribute to the creation of healthier and more resilient cities.

5.2. Environments

As Table 3 demonstrates, the environmental and sustainability domain within smart city research encompasses a highly detailed and urgent spectrum of agendas aimed at protecting public health and ensuring long-term ecological balance across four critical subdomains: air pollution, noise pollution, waste management and water resources.

Smart city Air Pollution research has rapidly evolved from static, fixed-station monitoring to data/model-driven spatiotemporal forecasting, and further toward operational governance integration (early warning, digital twins, participatory monitoring) and equity/policy alignment. Early work applied ML to pollution and weather data for air quality index (AQI) reporting and prediction (Popa et al., 2021). Forecasting then shifted to deep spatiotemporal models, notably Convolution Neural Network-LSTM (CNN–LSTM), for Particulate Matter 2.5 (PM2.5) prediction and broader DL approaches for multi-pollutant prediction (Bekkar et al., 2021; Huang & Kuo, 2018), with neighbourhood-scale ML evidence supporting fine urban deployment (Wai & Yu, 2023). Recent studies emphasise optimisation and robustness via LSTM-based deep random subspace learning (Sun & Xu, 2019), Particle Swarm Optimisation–LSTM–RNN (Dalal et al., 2024), chi-square feature selection (Mengash, Hussain, et al., 2022), Q-learning optimisation of inputs/lags

Table 3
Key analysis in environment domain.

Subdomain	Key concepts	Contents	Articles
Air Pollution	Forecasting	Non-linearity: Smart city air quality prediction should capture nonlinear temporal dynamics and pollutant–meteorology interactions through hybrid DL architectures, because conventional or single-stream models are often insufficient for short-term urban forecasting.	Huang and Kuo (2018); Bekkar et al. (2021); Binbusayyis et al. (2024); Dalal et al. (2024); Shaban et al. (2024)
		Multimodal Information: Predictive performance depends not only on model architecture, but also on spatial dependency, optimisation, and multimodal information, since urban air pollution is shaped by neighbouring stations, geographic structure, sparse monitoring networks, and heterogeneous data sources.	Sun and Xu (2019); Chang et al. (2020); Schürholz et al. (2020); Wai and Yu (2023); Chang-Silva et al. (2023); Njaime et al. (2025)
	Monitoring	Real-time Operation: Smart city air quality systems should move beyond static observation toward continuous, real-time, and operational monitoring, supported by IoT sensing, mobile devices, and resilient data handling.	Dutta et al. (2019); Montanaro et al. (2022); Khan et al. (2022); Alnowaiser et al. (2024)
		Event-aware Processing: Effective smart city monitoring requires not just sensor deployment, but also interpretable analytics and event-aware processing, so that large pollutant streams can be translated into understandable and actionable information.	Mengash, Hussain, et al. (2022); Kumar, Chandra, and Agarwal (2024); Mehmood et al. (2025)
	Decision-support	Early Warning and Operational Decision-support: Forecasting and monitoring become most valuable when embedded in early warning and operational decision-support systems, rather than treated as standalone analytical outputs.	Popa et al. (2021); Shahbazi et al. (2024); Naveed et al. (2025); Al-Enezi et al. (2025)
		Environmental Justice: Air quality research in smart cities is also a governance, equity, and system-design problem, because effective air quality management depends on environmental justice, climate-policy alignment, and citizen-centred monitoring coverage rather than on technical prediction alone.	Krupnova et al. (2022); Ulpiani et al. (2025); Sokolova et al. (2025)

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Table 3 (*continued*)

Subdomain	Key concepts	Contents	Articles
Noise Pollution	Monitoring	Crowdsensing: Smart city acoustic-pollution assessment should move beyond sparse fixed stations toward real-time, fine-grained, participatory sensing, especially where conventional monitoring is costly or spatially limited.	Zamora et al. (2018)
		Low-cost Mobile Sensing and Noise Characterisation: Acoustic monitoring should not only record sound levels but also support dynamic mapping and source-aware urban interpretation through dedicated embedded systems.	Hernandez-Jayo and Goñi (2021)
Waste Management	Classification & Processing	Automated Waste Image Classification: Smart city waste systems should move beyond manual segregation toward image-based, real-time, automated classification, because traditional collection and sorting are labour-intensive, slow, and environmentally inefficient.	Cheema et al. (2022); Al Duhayyim (2023); Lingaraju et al. (2023); Belsare et al. (2024); Thamarai and Naresh (2023); Gude et al. (2024)
	Smart bins & Operational optimisation	Operation: Smart city systems should not only classify waste but also support real-time monitoring, route optimisation, low-power sensing, and autonomous municipal response, because fixed schedules cause under-collection, overflow, and unnecessary cost.	Lingaraju et al. (2023); Sus-Bin / Bou-Rabee et al. (2025)
	Integrated / review / System-level faming	Broader System: AI in smart city waste management should be understood not only as a classification tool but as part of an integrated ecosystem spanning monitoring, sorting, logistics, waste generation modelling, recycling, waste-to-energy, and illegal dumping control.	Fang et al. (2023); Rathi & Gola (2024, smart city review sections on waste and infrastructure)
Water Management	Quality assessment & Predictive treatment	AI-enabled Treatment: Smart cities need predictive, data-driven, and uncertainty-aware water management, because conventional testing and treatment are often too static, infrastructure-heavy, or poorly suited to complex urban water systems.	Barzegar et al. (2023); Miao et al. (2021)
	Distribution systems, Infrastructure & governance	Multi-dimensioned Integrated Solution: Smart city water systems must be approached as infrastructure, governance, and decision-support problems, not only as prediction tasks, because sustainable urban water management depends on leak detection, reliability, reuse, monitoring, smart metering, blue-green infrastructure, and institutional coordination.	Rathi and Gola (2024)

(Chang et al., 2020), fault-tolerant monitoring (Khan et al., 2022), and K-Nearest-Neighbours (KNN)-imputation + ensemble IoT frameworks (Alnowaiser et al., 2024).

In parallel, early-warning and decision-support framing has strengthened: real-time forecasting architectures explicitly target early warning for sustainable smart cities (Shaban et al., 2024), graph-based spatiotemporal systems connect forecasting to health-risk monitoring, and broader decision-support/early-warning system designs are positioned as core smart city crisis management infrastructure (Al-Enezi et al., 2025). Data scarcity and transparency concerns also drive multimodal and explainable directions: transfer learning with multimodal data (including satellite) improves generalisation where ground stations are sparse (Njaime et al., 2025), while Vision-AQ fuses imagery and pollutant data and uses Gradient-weighted Class Activation Mapping (Grad-CAM) to improve interpretability and trust (Mehmood et al., 2025). Governance-oriented extensions include predictive urban digital twins (Naveed et al., 2025), citizen-feedback + real-time IoT support for government monitoring (Montanaro et al., 2022), CEP-based streaming alerts (Kumar, Chandra, & Agarwal, 2024), monitoring-system design balancing investment and user satisfaction (Sokolova et al., 2025), and IoT monitoring linked to health correlation (Dutta et al., 2019). Finally, environmental justice critiques warn AI monitoring can reproduce spatial inequities (Krupnova et al., 2022), while policy work highlights co-benefits from aligning air quality management with climate-neutrality strategies (Ulpiani et al., 2025).

Noise Pollution is an important sustainability challenge in smart cities due to its documented impacts on sleep quality, psychological well-being, and cardiovascular health (Hernandez-Jayo & Goñi, 2021; Zamora et al., 2018). Recent research highlights a shift from expensive, static monitoring systems toward scalable IoT-based sensing architectures. The sensing framework utilises smartphone-based crowdsensing with context-aware, energy-efficient sampling to generate real-time urban noise maps (Zamora et al., 2018). Similarly, the ZARATAMAP project deploys low-cost embedded acoustic nodes on electric bicycles to collect geo-referenced noise data and classify dominant noise sources (Hernandez-Jayo & Goñi, 2021). Together, these approaches demonstrate the transition toward dynamic, data-driven, and intelligent acoustic governance in smart cities.

Beyond atmospheric conditions, urban sustainability increasingly addresses sanitation and resource challenges through intelligent Waste and Water Management. In solid waste systems, IoT- and vision-based DL enable automated monitoring and classification. An IoT-Wireless Sensor Networks (IoT–WSN) monitoring framework combining wavelet transform and CNN outperformed KNN in classifying domestic, medical, and e-waste (Belsare et al., 2024), while broader reviews report that AI improves sorting, logistics optimisation, and illegal dumping detection with measurable cost and distance reductions (Fang et al., 2023). Optimised DL models have achieved over 99% classification accuracy (Al Duhayyim, 2023). Real-world implementations include

CNN-based waste-to-energy household systems (Thamarai & Naresh, 2023) and Long-range Wide Area Network-enabled, battery-free smart bins with energy harvesting and route optimisation (Bou-Rabee et al., 2025). Edge-based frameworks further enhance real-time segregation efficiency (Cheema et al., 2022; Gude et al., 2024).

In Water Management, intelligent analytics support both drinking water safety and sewage treatment. A Mamdani fuzzy inference system effectively integrates multiple water quality parameters under uncertainty (Barzegar et al., 2023). IoT-enabled sewage systems applying GRU, LSTM, and Support Vector Regression models demonstrate strong chemical oxygen demand prediction performance, with GRU performing best (Miao et al., 2021). Reviews of smart water distribution highlight IoT-based leak detection and operational optimisation as essential components of sustainable governance (Rathi & Gola, 2024). Overall, the literature points toward integrated IoT–edge–AI infrastructures that improve efficiency, environmental performance, and public health resilience in smart cities.

The literature reports mixed findings regarding the effectiveness of AI models for healthcare and environmental management. While advanced ML and DL techniques have demonstrated strong capabilities in prediction, monitoring, and decision support, model performance varies considerably depending on data characteristics, application contexts, and urban conditions (Bhute et al., 2024; Gong et al., 2023; Wu et al., 2022). Furthermore, although AI is increasingly applied to support proactive health management and environmental sustainability, researchers consistently warn that data biases, class imbalance, incomplete records, and unequal digital access may distort predictions and reinforce existing social and health inequalities (Brisimi et al., 2018; Tripathy et al., 2023; Wu et al., 2022). While recent studies advocate explainable AI, privacy-preserving techniques, and improved data governance to address these issues, limited research has examined how technical solutions can be systematically integrated with broader concerns of environmental justice, equity, and responsible urban governance. This gap highlights the need for more holistic frameworks that connect AI performance with societal and governance outcomes.

To address increasingly complex sustainability challenges, environmental monitoring in smart cities is shifting from sparse, expensive reference-grade stations toward dense, connected IoT and crowdsensing ecosystems, enabling wider coverage at lower cost and energy (Mehmood et al., 2025; Trigkas et al., 2025; Zamora et al., 2018). In parallel, analytics is moving from single-source sensor streams to multimodal and transferable learning, combining ground sensors with imagery/remote sensing and improving generalisation where stations are sparse (Mehmood et al., 2025; Njaime et al., 2025). Sustainability-oriented reviews further highlight a push toward edge intelligence and integrated ML/IoT–DL infrastructures to reduce computation/communication overhead and support SDG-aligned urban services, increasingly linked to digital twin/metaverse planning while noting persistent interoperability and governance challenges (De Las Heras et al., 2020; Khan et al., 2023; Lifelo et al., 2024; Trigkas et al., 2025).

5.3. Modelling

On the modelling dimension, Table 4 identifies four subdomains of state-of-the-art AI modelling and the dataset used. The first subdomain is Time-series Forecasting, which is primarily employed to address environmental challenges such as air quality prediction, weather and temperature forecasting, and thermal comfort estimation. Numerous studies have verified that LSTM-based models outperform a variety of DL architectures for environment forecasting (Dalal et al., 2024; Dey, 2024; Sekhar et al., 2024). Furthermore, as demonstrated by Faydi et al. (2023) and Pereira and Tamilselvi (2024), hybrid models that fuse LSTM with CNN or Graph Neural Networks (GNNs) architectures exhibit strong predictive performance by incorporating geospatial contextual information.

The second subdomain involves Classification tasks using signal, image, and acoustic data for human activity recognition or event detection. CNN are the most widely used models for classification, applied not only to image-based tasks (Azizian et al., 2024; Chauhan et al., 2023) and to voice anonymisation (Cohen-Hadria et al., 2019) and network signal classification (Lee et al., 2021; Moshiri et al., 2021). In the domain of waste management, real-time classification systems frequently employ YOLO-based models, which demonstrate strong performance in detecting and categorising waste materials Maske et al., 2025; Parimala Devi et al., 2025; Salian et al., 2025). In addition to DL approaches, tree-based models, particularly Random Forest, have also achieved competitive performance across various urban analytics classification tasks (Albeshri, 2021; Almadhor et al., 2024; Rao et al., 2025).

The third subdomain involves Optimisation models. The most representative ML approach for optimisation is Reinforcement Learning (RL). For example, Wang and Ni (2024) applied RL to optimise healthcare-service selection based on Quality-of-Service (QoS) metrics. In addition, various optimisation procedures, such as GridSearch and Simulated Annealing (SA), are frequently used to tune model parameters and enhance predictive performance (Alam et al., 2024; Zhu et al., 2024). The final subdomain comprises Generative Models which have recently gained significant attention. Image-generation and text-to-image models, such as Stable Diffusion, are increasingly applied in urban-design tasks and risk-management simulations (Albadrani, 2025; Narne, 2025). Notably, Jauhiainen et al. (2026) demonstrated that synthetic personas created using Large Language Models (LLMs) can support urban digital-twin architectures, offering a novel paradigm for urban-planning and design processes.

A notable trend within the modelling domain is the shift from models focused solely on improving numerical accuracy to approaches that incorporate multi-modal data and contextual information. Recognising the limitations of models trained exclusively on historical datasets, recent studies have introduced multi-modal frameworks that integrate meteorological variables, geographic context, and neighbouring-station data to enhance predictive performance (Ghose et al., 2022; Mehmood et al., 2025; Rana & Kumar, 2026). Correspondingly, new model architectures have gained prominence, including CNN–LSTM hybrids that effectively capture both spatial and temporal dependencies (Dey, 2024; Faydi et al., 2023; Pereira & Tamilselvi, 2024; Revathi et al., 2025). In addition, GNN and Transformer-based models are increasingly adopted to represent the complex spatiotemporal structures inherent in urban environments (Alnowaiser, 2025; Bhattacharya et al., 2024; Mishra et al., 2025). Advances in data availability have further enabled the use of multimodal datasets in AI models. For instance, Chen et al. (2021) combined traffic-sensor data with geo-tagged Twitter text to detect traffic events, capturing social behaviour through natural-language information. Similarly, Azizian et al. (2024) integrated gas-sensor readings with thermal-imaging data to improve gas-leak detection using CNN-based methods. In addition, semantic understanding is an increasingly important direction in AI development, particularly as multimodal models advance and language models become more widely adopted. Models such as mBERT and CNN are used to capture richer semantic relationships within complex textual tweets data (Chen et al., 2021; Tahir & Mehmood, 2025). In summary, incorporating real-world contextual and semantic information, through either hybrid DL architectures or multimodal datasets, enhances the capacity of AI systems to address practical urban challenges, moving beyond the limitations of models reliant solely on conventional numerical inputs.

While advanced AI models have demonstrated considerable potential across urban applications, the literature identifies persistent limitations related to bias, uncertainty, and explainability. Studies applying time-series and machine learning models report concerns regarding overfitting, generalisability, and the influence of biased training data on model performance (Dalal et al., 2024; Mishra et al., 2025; Nguyen et al., 2022). As generative AI technologies become increasingly prevalent in urban applications, these limitations have raised broader concerns regarding their responsible use. For instance, Narne (2025)

Table 4
Key analysis in modelling domain.

Subdomain	Key concept	Model	Dataset	Articles
Time-series Forecasting	Air quality, air quality index, air pollutants ($PM_{2.5}$, NO_2, O_3)	Particle Swarm Optimisation (PSO)-**LSTM-RNN**	Online air pollution monitoring dataset (Salt Lake City, USA)	Dalal et al. (2024)
		GNN-CNN, RF, LSTM	Kaggle air quality metrics (PM2.5, PM10, CO, NO2, etc.)	Mishra et al. (2025)
		1D-CNN + Bi-GRU, DLSTM, SVR, ARIMA	New South Wales (Australia) air quality dataset	Ghose et al. (2022)
		LSTM, GRU, **CNN-LSTM**	Beijing Municipal Environmental Monitoring Cent (Kaggle dataset)	Faydi et al. (2023)
		Deep Feed-Forward Neural Network (DL), SVM, NN, GLM	CityPulse EU FP7 Project dataset	Ghoneim and Manjunatha (2017)
		Particle Swarm Optimisation (PSO)-LSTM, SVR, GBT	Taiwan air quality and weather data from Environmental Protection Agency (EPA), Central Weather Bureau (CWB), and local station dataset (LSD)	Nivedita et al. (2025)
		CNN-LSTM, Bi-GRU, Bi-LSTM, GRU, CNN, LSTM	New Delhi pollution monitoring stations data	Pereira and Tamilselvi (2024)
		Deep learning Transformer Network (D-ATN), ARIMA, XGBoost, RF, LSTM, Transformer	Central Pollution Control Board (CPCB) dataset (Delhi, Mumbai, Bengaluru, Chennai, Kolkata)	Rana and Kumar (2026)
		RNN, CNN, **LSTM**, GRU	Beijing air quality dataset; Jena temperature dataset	Sekhar et al. (2024)
		Customised stacked-based LSTM (CSLSTM)	Air quality dataset (India cities 2015–2020) from Kaggle	Dey (2024)
		KNN, Decision Treen, SVR, **Random Forest**, ANN	Open Data Barcelona (NO2 concentrations and meteorological data)	Soriano-Gonzalez et al. (2024)
	Weather and temperature	**AtBiGRU**, BiGRU, GRU, CNN, PCA	Pesticide data from FAO, weather data from World Data Bank and Kaggle	Gupta et al. (2025)
		RNN, **LSTM**, AR, MA, Regression	Temperature from NASA-POWER – prediction of worldwide energy resources	Nguyen et al. (2022)
	Mortality rate	**Feature Selection Regression based on Neighbourhood Component Analysis (FSRNCA)**, Functional Link Artificial Neural Network (FLANN)	Big Cities Health Inventory (BCHI); diabetes, liver, protein localisation, and breast-cancer and primary-tumour	Kumar, Singh, and Kim (2024)
	Traffic accident severity	GNN, LSTM, MLP, **SHAP XAI**	US road accident dataset (Kaggle), UK Road Accident dataset	Alnowaiser (2025)
	Traffic noise	**Bi-Directional RNN**, GRU, LSTM	Blansko (Czech Republic) roundabout video and audio data	Zhang et al. (2021)
Image or Signal Classification	Human activity recognition	**RF**, RNN	Custom 100,000 sample Wi-Fi RSSI/Noise Floor dataset (VIT-AP University)	Rao et al. (2025)
		DL, Generalised Linear Model (GLM), Random Forest (RF), AdaBoost	UCI dataset, 30 people aged between 19 and 48 years old, HAR dataset	Albeshri (2021)
		CNN	Channel State Information (CSI) dataset	Moshiri et al. (2021)
		LSTM	Smart watch sensor data (gyroscope and accelerometer)	Kandpal et al. (2023)
	Waste or sewage management	**YOLOv3.0**	Custom dataset of manhole images	Kesharwani et al. (2024)
		YOLOv8 (CNN)	Manual labelling operations produced more than 3500 waste photographs	Maske et al. (2025)
		YOLOv7	Clean and Dirty Containers in Montevideo (Kaggle)	Salian et al. (2025)
		ResNet34 (CNN)	Waste image database (25,077 photos), real-world complex images	Chauhan et al. (2023)
		YOLOv5	Custom labelled waste dataset (Plastic, Paper, Metal, Organic)	Parimala Devi et al. (2025)
	Environmental comfort and sensation	**Tree Classifier**, MLP, Naive Bayesian	American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) RP-884 standard dataset	Almadhor et al. (2024)
		DNN, 1D CNN, RF, SVC, Decision Tree	ASHRAE Global Thermal Comfort Database II	Cakir and Akbulut (2022)
		ResNet50 CNN + MLP, Grad-CAM (XAI)	Air Pollution Image Dataset from India and Nepal (12,240 images), CPCB pollutant data	Mehmood et al. (2025)
		CNN, RNN, CNN-**LSTM**	Open-source audio datasets (TUT Acoustic Scenes, FSD50K)	Revathi et al. (2025)
		Perceptually Weighted FLANN, PSO	Stockholm Sweden water fountains dataset; Raman Global University lab dataset	Brahma et al. (2023)
	Event detection	**Multi-modal GAN**, LSTM_RNN, CNN	Caltrans PeMS (traffic sensor data); Geo-tagged Twitter dataset	Chen et al. (2021)
		U-net (CNN)	SONYC (Sounds of New York City) dataset; VoxCeleb; LibriSpeech	Cohen-Hadria et al. (2019)
		Multi-class classification-based Intrusion Detection Model (M-IDM), CNN, SVM, NB	National Cancer Center South Korea network data (electrocardiogram, thermometers, etc.)	Lee et al. (2021)

(*continued on next page*)

Table 4 (*continued*)

Subdomain	Key concept	Model	Dataset	Articles
		ResNet-50, K-Nearest Neighbours (KNN), Normalised Synthetic Minority Over-sampling Technique (NSMOTE)	Seven different gas-detecting sensors and thermal imaging camera	Azizian et al. (2024)
		Attention-based Generative Adversarial Network (ABGAN) with multi-objective interactive honeybee mating optimisation (MOIHBMO)	Real-time dataset from Saudi Arabia (1386 images)	Alsalamah (2023)
	Image watermarking	**DNN, PCA**	Ten standard colour images (Lena, Peppers, etc.), healthcare datasets from wearable devices	Pandey and Jaiswal (2024)
Optimisation	Human activity recognition	**Feedforward Deep Neural Network (FDNN), GridSearch**	Human Activity Recognition Dataset for Machine Learning (HARTH)	Alam et al. (2024)
	Urban planning modelling	**GNN + Simulated Annealing (SA)**	Urban infrastructure graph data, social network data, GIS, transportation databases	Zhu et al. (2024)
	Healthcare service selection	**Deep Reinforcement Learning (DRL)**	QWS dataset (2507 web services), Chronic Blood Pressure disorder dataset	Wang and Ni (2024)
Generative Model	Urban design simulation	**DALL•E 3, Stable Diffusion XL**	Site-specific environmental data (Riyadh), Native vegetation typologies, Copernicus Global Land Services, WorldClim v2.1	Albadrani (2025)
	Digital Twin architecture	**ChatGPT-5.1, Nanobanana Pro**	DigitalTurku (Synthetic Personas for Urban Digital Twin of Turku, Finland)	Jauhiainen et al. (2026)
	Urban risk management application	**GAN, Variational Autoencoders (VAE)**	CCTV footage, Traffic sensors, Geospatial data, Social media	Narne (2025)

* Bold: best performance model.

highlighted that Generative Adversarial Networks (GANs) and Variational Autoencoders (VAEs) can inherit and amplify biases embedded within training data, potentially leading to distorted predictions and outcomes. Likewise, Jauhiainen et al. (2026) identified several challenges associated with LLM-generated synthetic data, including limited data transparency, uncertainty regarding data completeness and accuracy, probabilistic inconsistencies, and the potential propagation of bias. While AI is widely promoted as a solution for improving urban decision-making and sustainability, comparatively fewer studies address how these technical limitations can be mitigated through responsible and ethical approaches. This gap highlights the need for greater integration between AI model development and responsible governance approaches to ensure reliable and equitable urban outcomes.

Overall, the reviewed studies demonstrate that AI provides effective solutions for promoting environmental sustainability and improving urban management. However, the focus of research is gradually shifting beyond the performance and efficiency of AI models toward addressing their limitations, particularly issues related to bias, uncertainty, and explainability. Consequently, there is growing emphasis on ensuring the responsible use and trustworthiness of AI systems within urban environments through the development of transparent, accountable, and ethically governed AI frameworks.

5.4. Synthesising insights

Numerous studies have addressed data limitations using a range of mathematical and technical approaches. Early research predominantly relied on historical logged datasets to develop time-series forecasting and image-classification models; however, both sensor-derived datasets and open repositories often suffer from sparsity, missing values, and limited generalisability (Dalal et al., 2024; Trigkas et al., 2025). To mitigate these limitations, many studies adopted enhanced preprocessing techniques, such as Principal Component Analysis (PCA) (Gupta et al., 2025; Maske et al., 2025) and correlation-based feature selection (Dalal et al., 2024; Ghose et al., 2022; Rana & Kumar, 2026), to refine input variables prior to model development. In addition, several studies employed Particle Swarm Optimisation (PSO)–a population-based stochastic optimisation algorithm capable of identifying optimal or near-optimal solutions in high-dimensional search spaces. PSO iteratively updates the position and velocity of particles based on their historical best performance and the global best within the search space (Dalal et al., 2024; Nivedita et al., 2025). Other studies addressed imbalance or bias in urban datasets through resampling techniques. For example, Azizian et al. (2024) utilised the Normal Synthetic Minority Over-Sampling Technique (NSMOTE), which generates synthetic minority-class samples using randomised interpolation to reduce dataset imbalance. Overall, while acknowledging the inherent limitations of urban data sources, a substantial body of research incorporates diverse preprocessing, optimisation, and resampling techniques to mitigate bias, enhance data quality, and extract meaningful information for AI-driven urban-analytics models.

Table 5 exhibits the core conceptual shifts of smart city and healthier city frameworks demonstrated by the key thematic findings. In the governance domain, four subdomains illustrate how digital governance is shifting from procedural, bureaucratic digitalisation toward integrated, data-driven, and participatory approaches. Digital platforms, crowdsourcing, and anticipatory decision-making are reshaping operational, institutional, and ethical practices in smart city management. In the environmental domain, studies focus on technological transitions in sensing and monitoring systems. Traditional sparse sensors are increasingly replaced by dense crowdsensing networks, while multimodal and transfer learning approaches improve the capture of geospatial context. Emerging edge intelligence and integrated IoT systems address communication and computational constraints. In the modelling domain, four key applications highlight methodological advances. Recent models incorporate multimodal datasets and semantic/contextual information, while diverse interpolation techniques are used to overcome sparse and heterogeneous urban datasets.

The emergence of AI has revealed a range of new challenges that cannot be adequately addressed by existing smart city or healthy city frameworks. Traditional smart city research has primarily focused on optimisation, sensing infrastructures, and economic efficiency as responses to rapid urbanisation (Afinowi, 2025; Allam et al., 2019; Almulhim & Yigitcanlar, 2025). In contrast, the Healthy Cities framework has generally approached digital technologies from a more limited perspective, concentrating on public healthcare applications and specific technological components such as sensing systems, IoT devices, and wireless networks (Brisimi et al., 2018; Kamel Boulos & Al-Shorbaji, 2014). However, the increasing adoption of AI has introduced novel challenges that extend beyond the scope of these established frameworks. These include prediction bias arising from the unequal distribution of sensors and data sources (Chen, 2025; Mehmood et al., 2025), a lack of explainability associated with the black-box nature of AI models (Krupnova et al., 2022; Mhlanga, 2022), and harm to privacy

Table 5
Shifts from conventional to AI-driven-smarter and healthier cities approaches.

Domain	Subdomain	Shift	
		From	To
Governance	- Integrative Governance System - Citizen Participation - Public Decision-making - Ethical and Responsible Governance	Procedural bureaucratic digitalisation Hierarchical, top-down governance Reactive governance	Integrative governance framework Participatory governance Data-centric, and anticipatory governance
Environment	- Air Quality - Noise Pollution - Waste Management - Water Management	Sparse, expensive, reference-grade sensing Single-source sensor stream Computation/ communication overhead	Dense, connected IoT and crowdsensing Multi-modal and transferable learning Edge intelligence and integrated ML/ IoT-DL infrastructure
Modelling	- Time-series Forecasting - Classification - Optimisation - Generative Model	Multi-modal model, semantic and contextual information, data interpolation	

(Bosco et al., 2026). Importantly, these challenges are closely linked to ethical and human-centred values such as responsibility, trustworthiness, accountability, fairness, and transparency (Albadrani, 2025; Bhattacharya et al., 2024; Bosco et al., 2026). Consequently, they require a broader multi-sectoral approach that incorporates the perspectives of diverse stakeholders, including governments, technology providers, researchers, communities, and citizens. These findings reinforce the need for the proposed concept of smarter and healthier cities, which seeks to capture the emerging challenges and opportunities associated with responsible AI deployment in urban environments.

Another important finding is the lack of an integrated perspective on the AI-driven transformation on smart city. Studies from developed countries, particularly those adopting governance and institutional perspectives, tend to address broad conceptual issues related to the responsible, ethical, and sustainable use of AI. However, they often provide limited insight into the specific technical solutions and AI models required to operationalise these objectives (Gallego-Álvarez et al., 2025; Mastrogiovanni, 2025). In contrast, studies employing field-obtained datasets and advanced AI models—predominantly conducted in developing countries and the Global South—demonstrate a wide range of practical applications and use cases for AI. Nevertheless, these studies often pay insufficient attention to institutional and governance dimensions of responsible AI, including bias mitigation, participatory decision-making, inclusiveness, and accountability (Albadrani, 2025; Bokhari & Myeong, 2022). Overall, the literature reveals a disconnect between the institutional and operational governance of AI and the development and application of advanced AI models. Despite their complementary nature, these two streams of research remain largely separate, highlighting the absence of a framework capable of bridging technological innovation and responsible urban governance.

6. Key findings and challenges

This study reveals the AI-driven conceptual transformation of smart and healthier cities and, in turn, proposes a key framework for smarter and healthier cities to guide the responsible use of AI in the urban sector. Fig. 4 presents the smarter and healthier cities framework derived from the systematic literature review. It synthesises the review process and key thematic findings and outlines the guiding principles for the responsible use of AI in advancing smarter and healthier cities, along with the corresponding challenges identified in the literature.

6.1. *Smarter and healthier cities framework*

The proposed smarter and healthier cities framework advances existing smart city and healthy city paradigms in three keyways. First, rather than merely integrating these two traditions, the framework captures the fundamental transformation of urban systems driven by recent advances in AI. AI has enhanced urban governance and management through greater efficiency, optimisation, automation, and data-driven decision-making, thereby making cities increasingly “smarter”. However, these advances have also introduced new challenges, including algorithmic bias, overfitting, a lack of explainability, privacy concerns, and insufficient ethical safeguards. Such transformations cannot be adequately understood through solely technological or institutional perspectives. Instead, they require a broader, multi-sectoral approach that considers the interactions between technological innovation, governance, environmental sustainability, and human well-being. Furthermore, the rapid evolution of the AI ecosystem, as illustrated in Fig. 2, necessitates a state-of-the-art research framework capable of capturing both emerging opportunities and challenges. By building upon the complementary strengths of smart city and healthy city concepts, the smarter and healthier cities framework provides a holistic lens through which AI-driven urban transformation can be understood and guided. In doing so, it enables the assessment of technological development and deployment not only in terms of efficiency and innovation, but also in relation to broader dimensions of human well-being, sustainability, inclusiveness, and responsible governance.

Second, the framework provides a cross-sectoral structure that connects previously fragmented domains and stakeholders through AI-enabled infrastructures. Compared with traditional smart city frameworks, the convergence with the Healthy Cities perspective broadens the scope beyond technological efficiency and infrastructure development to encompass human well-being, social inclusion, and environmental sustainability. As a result, the proposed framework incorporates a wider range of stakeholders and domains that are critical to responsible urban development. As demonstrated in Section 4, this integration occurs across multiple dimensions, including actors and institutions (Section 4.1), systems and managers (Section 4.2), and data sources and analytical processes (Section 4.3). By explicitly linking these elements, the framework moves beyond conceptual synthesis and provides an integrated perspective on how AI reshapes interactions among technological systems, urban processes, and social actors. In doing so, it offers a comprehensive foundation for understanding and governing AI-driven urban transformation in a responsible, sustainable, and human-centred manner.

Third, the smarter and healthier cities framework serves as a bridge between theoretical and qualitative perspectives and empirical and quantitative approaches. As demonstrated in both the geographical and thematic analyses in section 4, the existing literature addresses AI-driven urban transformation through largely separate perspectives, including institutional and governance-oriented studies on the one hand, and technological and application-oriented studies on the other. While governance-focused research emphasises responsible AI, ethical considerations, and institutional arrangements, technology-focused studies primarily investigate the development and application of advanced AI models. The smarter and healthier cities framework explicitly recognises this divide and provides a conceptual foundation for connecting these complementary research streams. By integrating institutional, operational, technological, and societal perspectives, the framework offers a new direction for translating responsible AI principles into practical urban applications while ensuring that technological innovation remains aligned with broader objectives of sustainability, inclusiveness, and human well-being.

6.2. AI-driven transformation toward smarter and healthier cities

According to the articles examining smarter cities and healthier cities through the lens of AI, we identified significant conceptual transformations. In governance, digitalisation has moved from procedural and bureaucratic processes toward integrated, participatory, and anticipatory systems. In the environmental domain, traditional sparse references grade sensors are being replaced by dense IoT-based crowdsensing capable of multimodal data collection and transferable model learning. Furthermore, sensing operations increasingly adopt edge intelligence architectures to manage computational and communication demands. We argue that these transformations are closely driven by advances in AI. For instance, the emergence of multimodal models enables more integrated systems, as they can incorporate diverse types of urban data from multiple sources, thereby fully leveraging dense IoT sensors or crowdsensing (Lifelo et al., 2024; Montanaro et al., 2022). By integrating heterogeneous datasets, contemporary AI models are increasingly capable of capturing contextual and semantic information. The growing use of GenAI, recently within urban practice applications, further underscores the importance of semantic and contextual understanding to capture the nuanced meaning, spatial context, and temporal realities of urban data (Jauhiainen et al., 2026;Lifelo et al., 2024; Mastrogiovanni, 2025). Additionally, various AI-based data imputation and interpolation techniques are now widely employed to overcome the inherent limitations of sensing infrastructures and to support digitalised governance processes (Afinowi, 2025; Binbusayyis et al., 2024; Faydi et al., 2023). Taken together, technological developments demonstrate that the conceptual transformation toward smarter and healthier cities is both enabled and accelerated by the rapid evolution of AI technologies.

6.3. Critical engagement of AI

While the literature largely portrays AI as a key enabler of smarter and healthier cities, an emerging body of research calls for a more critical engagement with its technical, governance, and societal implications. One of the most frequently discussed concerns relates to the governance implications of AI-enabled decision-making. Several studies highlight risks associated with algorithmic bias, transparency deficits, and accountability gaps, all of which may undermine fairness, explainability, and public trust in AI-driven governance processes (Lifelo et al., 2024; Mastrogiovanni, 2025; Mhlanga, 2022). The black-box nature of many AI systems complicates the interpretation and justification of decisions, particularly in contexts that directly affect citizens' well-being. Consequently, the literature increasingly emphasises the importance of explainable, trustworthy, and responsible AI frameworks capable of balancing system performance with transparency, fairness, accountability, and public confidence.

The review also reveals a number of persistent structural and contextual constraints that may hinder the effective implementation of responsible AI in practice. Beyond technical safeguards, many cities continue to face infrastructural limitations, fragmented regulatory environments, resource constraints, and socio-cultural barriers that affect technology adoption and governance capacity (Joseph, 2025). These challenges are particularly evident in developing regions, where institutional capacity and digital infrastructure may be insufficient to support the governance requirements of advanced AI systems. Therefore, AI-enabled urban transformation cannot be understood solely as a technological issue; it must be analysed within broader governance, institutional, and societal contexts. Existing studies suggest that responsible AI deployment requires integrated governance frameworks in which ethical oversight, citizen participation, data governance, and urban decision-making operate as interdependent and mutually reinforcing components (Rasoulzadeh Aghdam et al., 2025; Almulhim & Yigitcanlar, 2025).

Finally, several studies raise concerns regarding digital inequality, data privatisation, technological concentration, and cybersecurity risks. The unequal distribution of digital infrastructure and sensor networks may reinforce existing social inequalities by producing biased or incomplete representations of urban environments (Chen, 2025; Krupnova et al., 2022). Similarly, the concentration of technological capabilities and large-scale data resources within a small number of corporations may create asymmetries in power, participation, and decision-making (Ehwi et al., 2022; Rasoulzadeh Aghdam et al., 2025). At the same time, the growing reliance on interconnected AI-enabled systems increases vulnerability to cybersecurity threats and data breaches, posing additional risks to critical urban infrastructures and public trust (Al-Besher & Kumar, 2022; Narne, 2025; Yigitcanlar et al., 2020). Collectively, these findings suggest that the transition toward smarter and healthier cities requires not only technological advancement, but also robust governance arrangements capable of addressing the ethical, institutional, and societal implications of AI-driven urban transformation.

6.4. Key challenges and guiding principles

The lower right section of Fig. 5 illustrates the core guiding principles designed to address the key challenges in advancing smarter and healthier cities. The AI-driven transformation of smarter and healthier cities faces multiple challenges, including governance and societal challenges such as algorithmic bias, digital divides; data-related challenges such as data acquisition, quality, privacy protection, and transparency; and technical challenges such as security, interoperability, explainability, and trustworthiness.

6.4.1. Technocracy - ethical safeguard

While the advancement of AI has enabled more participatory and efficient forms of digital urban governance, it is not a panacea for achieving smarter and healthier cities. Conventional smart city models are largely grounded in a technocratic logic that prioritises technological integration, data streams, and digital systems as primary means of enhancing urban functionality, accessibility, efficiency, and competitiveness (Hammoumi et al., 2024; Kumar et al., 2022). However, such a technocratic orientation often underestimates the governance and societal challenges of AI-driven systems, leading to the neglect of citizens' and local communities' needs within top-down, corporate-driven models of smart city development (Almulhim & Yigitcanlar, 2025). These limitations highlight that technological advancement alone does not automatically produce inclusive, equitable, or sustainable urban outcomes.

Ethical concerns in AI-enabled urban governance are not peripheral issues but central challenges that arise across multiple dimensions, including algorithmic design, data use, and institutional decision-making processes (Almulhim & Yigitcanlar, 2025; Ehwi et al., 2022; Hammoumi et al., 2024). Rather than being treated as secondary considerations, they underscore the need to rethink the normative foundations of smart city development. In this context, AI in smart city applications requires balancing innovation with responsible governance through oversight and guidelines, as ethical and regulatory risks alongside technical limitations such as scalability and computational constraints may otherwise hinder its sustainable development and effectiveness (Lifelo et al., 2024). Accordingly, developing context-specific regulations and legal frameworks is crucial to ensure that technological progress remains consistent with societal values and established legal principles (Lifelo et al., 2024).

Consequently, ethical governance functions as a necessary safeguard against the limitations of technocratic smart city models, ensuring that AI-enabled urban systems remain attentive to issues of justice, accountability, and social legitimacy, rather than being driven solely by technological performance metrics.

6.4.2. Data bias – environmental justice

In the practical deployment of AI-driven urban-monitoring systems, data biases can significantly undermine the reliability and fairness of

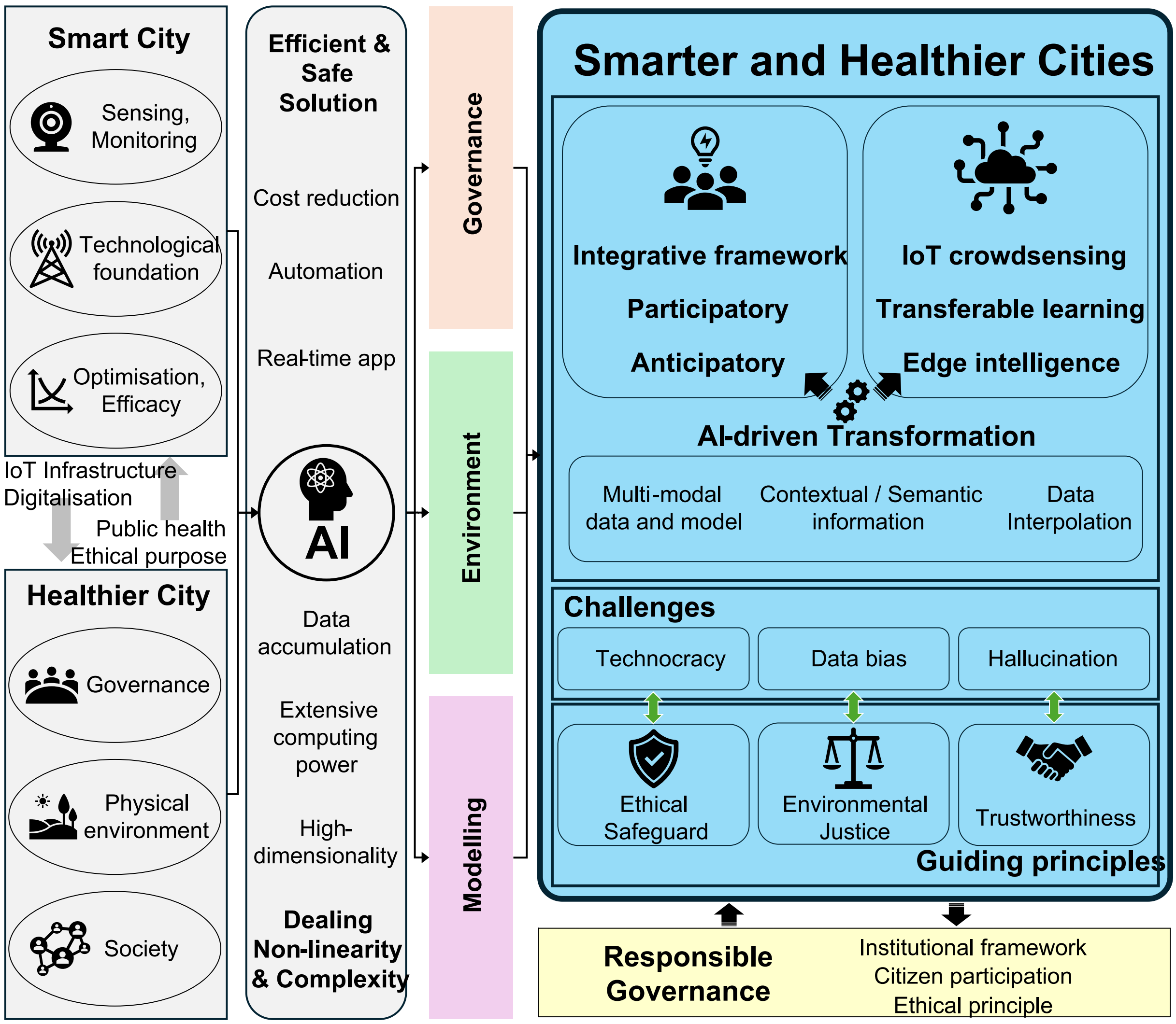

Fig. 5. Conceptual framework for smarter and healthier cities: Integrating AI-driven transformations, emerging challenges, and guiding principles.

decision-making in smarter and healthier cities. Although AI is increasingly applied in urban governance and environmental management, it simultaneously introduces substantial risks, particularly those arising from data bias and unequal representation, which in turn heighten the potential for environmental injustice. For example, sensor networks and smartphone-based crowdsourcing initiatives tend to be disproportionately concentrated in affluent, highly connected urban areas, leaving low-income and marginalised neighbourhoods largely unmonitored (Alnowaiser et al., 2024). Furthermore, the failure of highly susceptible low-cost sensors can introduce additional data biases, necessitating rigorous calibration procedures to maintain scientific validity (Mehmood et al., 2025). When AI models are trained on such geographically skewed datasets, they systematically underestimate the public-health risks faced by vulnerable communities (Alnowaiser et al., 2024), ultimately reinforcing inequalities rather than alleviating them.

To mitigate inclusiveness and environmental justice issues derived from data bias, AI systems must draw upon diverse, multi-source datasets that capture the wide spectrum of urban experiences. The literature emphasises that data inclusiveness is essential because reliance on biased or incomplete data, such as retrospective hospital records with missing values and inconsistent documentation, can distort AI predictions and reinforce existing inequalities (Tripathy et al., 2023). These risks are further exacerbated by the digital divide, which can exclude marginalised and vulnerable populations from AI-enabled healthcare services (Cook et al., 2018; Cruz-Castañeda & Bertemes-Filho, 2024). Since these populations are also disproportionately exposed to urban health hazards, addressing data inclusiveness is fundamental to advancing environmental justice (Allam et al., 2019; Brisimi et al., 2018). Leveraging cross-sectoral data enables AI models to better reflect the heterogeneity of urban populations and reduce systematic blind spots (Allam et al., 2019; Kaginalkar et al., 2023). However, responsible AI requires more than simply expanding data volume. Qualitative and contextual dimensions of urban life must also be incorporated into AI systems to ensure that predictions and recommendations are meaningful within specific social, cultural, and spatial settings (Hantrais & Lenihan, 2021; Schürholz et al., 2020). In moving toward smarter and healthier cities, responsible AI must therefore integrate both multi-source datasets and rich contextual understanding—elements that cannot be generated by algorithms alone. These practices are essential for mitigating data bias, promoting inclusiveness, and ensuring that AI-driven urban solutions advance environmental justice.

6.4.3. *Hallucination - trustworthiness*

The inherent black-box nature of many AI models (Yigitcanlar et al., 2020) poses significant challenges for transparency and explainability. Limited explainability and uncertainty undermine trust and credibility, creating major barriers to AI adoption in urban contexts (Jauhiainen et al., 2026; Krupnova et al., 2022). One consequence of this opacity is the generation of incorrect or fabricated outputs, commonly referred to as hallucinations, which may lead to inappropriate or harmful decisions in high-stakes domains such as public policy and urban governance (Lifelo et al., 2024; Mastrogiovanni, 2025). Such risks are particularly concerning because urban decision-making depends on reliability, accountability, and public trust.

These concerns are further intensified by the rise of generative AI. Narne (2025) and Jauhiainen et al. (2026) argued that generative AI systems may produce distorted outcomes due to limited data transparency, uncertainty, and biases embedded within training datasets. Consequently, scholars increasingly emphasise the need for governance frameworks capable of assessing, communicating, and managing AI-related risks in a responsible manner.

In response, a growing body of literature advocates the adoption of trustworthy AI as a guiding framework for responsible AI deployment in urban environments (Lifelo et al., 2024; Mastrogiovanni, 2025). In particular, the European Union's Ethics Guidelines for Trustworthy AI (High-Level Expert Group on Artificial Intelligence, 2019) outlines a set of principles designed to ensure that AI systems remain trustworthy and human-centred. These principles include human agency and autonomy, technical robustness and safety, privacy and data governance, transparency, diversity and fairness, and accountability (Bosco et al., 2026; Gallego-Álvarez et al., 2025). Accordingly, trustworthy AI has emerged as a critical foundation for mitigating the risks associated with advanced AI systems while promoting their responsible and sustainable use in cities.

A key element of trustworthy AI in urban governance is the ability to evaluate and communicate the credibility of model outputs. Because AI systems may generate inaccurate predictions or hallucinations, decision-makers must be informed of the reliability and limitations of the models they employ (Lifelo et al., 2024; Mastrogiovanni, 2025). In this regard, uncertainty quantification through probabilistic and knowledge-based AI approaches offers a promising solution (Yigitcanlar et al., 2020). Providing numerical measures of confidence alongside AI-generated predictions enables urban authorities to determine when model outputs should be trusted, questioned, or supplemented with additional evidence. Such transparency not only reduces the risk of overreliance on AI systems but also supports more accountable, context-sensitive, and evidence-based urban decision-making by allowing practitioners to anticipate multiple scenarios and assess potential risks more effectively.

6.5. Emerging trends and broader implications

We identified several valuable findings that highlight promising AI-enabled or AI-accelerated developments, although not directly incorporated into the main research framework, that offer important implications for the future direction of smarter and healthier cities.

First, in the healthcare sector, there is an evident shift toward anticipatory and preventive health systems supported by IoHT-based sensing infrastructures. IoHT devices capture continuous physiological and contextual data (Abdeen et al., 2022; Cook et al., 2018; Obinikpo & Kantarci, 2017), enabling remote, patient-centred management (Chen et al., 2020; Ghazal et al., 2021). Edge, mist, and fog architectures further support low-latency preprocessing (Nagarajan et al., 2021; Rathi et al., 2021; Tripathy et al., 2023), while lightweight edge models enhance real-time analytics and scalability (Cruz-Castañeda & Bertemes-Filho, 2024; Wu et al., 2022). AI underpins this paradigm by integrating large-scale IoHT streams with digitised clinical records and multimodal biomedical data to produce predictive models and automated decision-support (Chui et al., 2017; Sowmitha et al., 2022). These capabilities enable early disease detection (Bhute et al., 2024; Mengash, Alharbi, et al., 2022), chronic-risk prediction (Brisimi et al., 2018), and the rapid identification of high-risk conditions (Farooq et al., 2017; Chen et al., 2020), collectively supporting a shift from reactive treatment to anticipatory, preventive urban-health systems (Chui et al., 2017).

Second, Blockchain–AI techniques strengthen the digitalisation of governance by enhancing cybersecurity. While cloud and edge infrastructures improve scalability, they also raise concerns regarding latency, privacy, and interoperability (Islam et al., 2017; Muhammed et al., 2018). Blockchain mitigates these risks through decentralised consensus, asymmetric cryptography, and immutable ledgers, including geospatially enabled designs for validating health events (Kamel Boulos et al., 2018). Hybrid blockchain–AI approaches using federated learning and homomorphic encryption further enable secure distributed analytics (Ali et al., 2023; Rahman et al., 2021).

Last, Digital Twin (DT) technologies increasingly enable the operation of smarter and healthier cities. By synchronising IoT sensing, AI analytics, and cloud platforms, DT systems generate dynamic virtual replicas that support disease progression modelling and early intervention (Abirami & Karthikeyan, 2023; Yang et al., 2021). At the urban scale, DT architectures integrate environmental exposures and biometric signals to deliver real-time health advisories (Jayachandran et al., 2025), reinforced by ISO/IEEE 11073 standards (Laamarti et al., 2020) and smart hospitals' gains in operational efficiency (Pradeep et al., 2024).

7. Conclusion

Since the emergence of the smart city concept in the early 2000s, societies have undergone profound social and technological transformations. During the process, there emerged both the limitations of technology-centred urban solutions and the dramatic evolution of AI. This study sought to articulate the concept of smarter and healthier cities, foregrounding the advancing technical capacities of AI.

Through a systematic literature review, this study synthesised two previously parallel strands of scholarship, smart city research and the healthier city tradition, and demonstrated that these paradigms are deeply interrelated, each compensating for the conceptual gaps of the other. Their convergence, further strengthened by recent advances in AI, creates new opportunities for addressing complex and interconnected urban challenges. Consequently, urban planners and decision-makers now require solutions that are not only technologically advanced but also capable of promoting healthier, more inclusive, and sustainable urban environments across multiple sectors.

The advancement of AI presents both significant opportunities and notable challenges for the pursuit of smarter and healthier cities. On one hand, AI's capacity to process non-linear, high-dimensional urban datasets and to support the digitalisation of governance makes it a particularly powerful tool for contemporary urban systems. On the other hand, as a substantial body of literature underscores, the risks associated with AI, ranging from bias and opacity to ethical concerns and unintended harm, necessitate its responsible and accountable use (Lifelo et al., 2024; Mastrogiovanni, 2025). Therefore, we argue that the development of AI-driven urban solutions must be grounded in robust ethical principles and supported by strengthened institutional frameworks, transparent and responsible governance mechanisms, and continuous technological refinement to ensure that innovation aligns with broader societal goals in the pursuit of smarter and healthier cities.

To sum up, this study contributes to the ongoing academic development of the smarter and healthier cities agenda by providing an integrated perspective on the relationship between technological innovation, urban health, and responsible governance and offering a conceptual foundation for future research. Future research should extend this discussion by incorporating additional dimensions that are becoming increasingly central to the evolution of AI-enabled urban systems, including cybersecurity, physical AI, and digital governance frameworks. Given the unprecedented pace of AI development, continuous monitoring of emerging technologies and systematic assessment of their societal, environmental, and governance implications are essential. As new AI technologies emerge, they introduce not only novel opportunities but also new risks and challenges that require ongoing scholarly and practical attention. Furthermore, the use of broader and more diverse datasets, together with interdisciplinary perspectives spanning urban studies, computer science, public policy, and related fields, will be critical for generating more generalisable and contextually grounded insights. As emphasised throughout this study, AI technologies should be evaluated not only from technical and operational perspectives, but also through ethical, social, and governance lenses to ensure their responsible deployment and to mitigate potential risks and unintended consequences. Ultimately, advancing this research agenda will be pivotal in ensuring that future cities are not only technologically advanced, but also healthier, more sustainable, inclusive, and socially responsible.

This study is subject to several limitations. First, although a systematic search strategy was employed, the selected databases and search keywords may not have captured the full breadth of relevant literature, potentially excluding studies that used alternative terminology or were indexed in other sources. Second, only English-language publications were included in the review, which may have limited the representation of perspectives from non-English-speaking regions and reduced the coverage of broader international contexts. Third, the review focused primarily on the governance, environment, and modelling domains identified within the literature. For instance, emerging literature suggests that AI is increasingly transforming design practices through applications in computer vision, automation, and generative design, indicating a promising direction for future research (Agboola, 2024). As a result, other relevant domains, such as urban design, planning, architecture, and related disciplines, were not examined in depth.

CRediT authorship contribution statement

Chulwoong Park: Writing – review & editing, Writing – original draft, Visualization, Resources, Methodology, Investigation, Formal analysis, Data curation, Conceptualization. **Kyounghee Cho:** Writing – review & editing, Writing – original draft, Methodology, Investigation, Data curation, Conceptualization. **Yeunsoo Park:** Writing – review & editing, Writing – original draft, Validation, Methodology, Investigation, Data curation, Conceptualization. **Mohammad Mayouf:** Writing – review & editing, Validation, Supervision, Methodology, Conceptualization. **Muhammad Afzal:** Writing – review & editing, Supervision, Project administration, Methodology, Investigation, Conceptualization.

Declaration of competing interest

The authors declare no conflict of interest.

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Data availability

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