International Journal of Innovative Research in Engineering and Management (IJIREM)
ISSN (Online): 2350-0557, Volume 13, Issue 5, Oct-Nov 2026
DOI: https://doi.org/10.55524/ijirem.2026.13.5.9
Article ID IJIR3237, Pages 73-83
www.ijirem.org

AI-Powered Smart Cities for Sustainable Development: Technologies, Frameworks, and Challenges

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Received: 20 Oct 2026; **Revised:** 2 Nov 2026; **Accepted:** 13 Nov 2026; **Published Online:** 18 Nov 2026

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ABSTRACT- Rapid urban growth is straining infrastructure, natural resources, and public administration, and this has made sustainable urban development one of the defining issues of the century. The present study examines how artificial intelligence (AI)-enabled smart city technologies support sustainability. Machine learning, computer vision, natural language processing, reinforcement learning, digital twins, explainable AI, and federated learning are covered, along with their use in transport, energy, waste, water, public safety, and e-governance. We put forward a five-layer conceptual framework made up of the Sensing, Data, Intelligence, Application, and Governance layers. The fifth layer, which cuts across the other four, provides the policy, audit, and accountability mechanisms on which trust in AI outputs and their responsible use depend. Initiatives in India and elsewhere are compared on qualitative criteria and, wherever dependable data are available, on measurable indicators such as water loss, irrigation savings, lighting energy savings, congestion, and travel time. The gains reported are encouraging, yet they are largely self-reported and cannot be compared directly, and no verified figures for emissions or waste management could be located. The paper also discusses privacy, bias, the digital divide, interoperability, and the energy footprint of AI itself, maps applications onto the Sustainable Development Goals (SDGs), and closes with policy recommendations and research directions.

KEYWORDS- Artificial Intelligence, Governance, Smart Cities, Sustainable Development Goals, AI-Powered Smart Cities

I. INTRODUCTION

The United Nations projects that close to seven in every ten people will be living in urban areas by 2050, a shift that will heavily burden transport, energy supply, water, and municipal services [1]. Even now, cities account for roughly 78 percent of global energy use and over 60 percent of greenhouse gas emissions, although they cover less than 2 percent of the Earth's land area [2]. Managing urban growth and city infrastructure with fixed rules is a poor fit for a problem of this scale. Out of this situation came the idea of the “smart city,” in which digital technologies are built into city infrastructure so that it runs more efficiently, adapts more readily, and is more convenient to use [3], [4].

AI now sits at the center of this change. Smart city technology in earlier generations depended mainly on automation and rule-based control. AI, on the other hand, draws on data from many sources, historical as well as real-time, and uses it to forecast and decide what should happen next [5], [6]. When paired with the Internet of Things (IoT), it enables a city to do more than run automatically; it can keep learning how to improve its own operation. This move from automation to self-optimization is what sets an AI-powered city apart from earlier e-governance models and from infrastructure control based on Supervisory Control and Data Acquisition (SCADA) [7].

Sustainability, however, does not follow automatically from digitalization. Consider a traffic system that eases congestion but depends on energy-hungry data centers, or a surveillance system that improves public safety at the expense of residents' privacy; both show that bringing AI into cities can create serious problems as well as benefits [8], [9]. This paper therefore asks a single central question: what technological and governance conditions allow AI adoption in cities to deliver sustainable development instead of simply more efficient operations?

Urban infrastructure has long been planned through periodic surveys, master plans, and centralized decisions that take years to reach. That method served reasonably well for twentieth-century urbanization, but it breaks down in cities where population, vehicle ownership, and energy demand can shift substantially within one budget cycle.

In parallel, sustainability has moved from the margins to the center of urban policy, mainly because the UN 2030 Agenda for Sustainable Development, with its seventeen Sustainable Development Goals (SDGs), was adopted in 2015 [10]. City administrations are now expected to report on sustainability indicators covering energy, emissions, water, and fair access to services. Meeting that expectation calls for detailed, continuous monitoring, which AI-enabled sensing and analytics are able to supply [11]. These two trends, growing urban complexity and the demand for sustainability accountability, provide the setting in which this paper studies AI-enabled smart city technology.

This paper makes four contributions. The first is a systematic organization of the scattered literature on AI-enabled urban technologies, including studies from 2024 and 2025. The second is a five-layer framework that keeps sensing, data, intelligence, application, and governance concerns apart, with an explicit account of what the fifth

(Governance) layer does. The third is a comparison of AI-powered smart city projects in developed and developing countries, India's Smart Cities Mission among them, using qualitative criteria and, where dependable data exist, measurable indicators. The fourth is a mapping of concrete smart city AI applications to specific SDGs, from which policy recommendations follow.

The remainder of the paper is arranged as follows. Section II sets out the research methodology, and Section III reviews the literature on smart cities and AI-driven urban technologies. Section IV covers the main AI technologies employed in smart cities, while Section V introduces the five-layer framework. Application areas and case studies appear in Section VI. Section VII offers the comparative analysis of selected global and Indian smart city projects, measurable indicators included. Section VIII takes up the principal challenges and ethical questions raised by AI-driven urban governance, and Section IX links the technologies to the SDGs. Section X proposes key performance indicators for assessing deployments, Section XI describes stakeholder roles, and Section XII presents policy recommendations. The limitations of the study are stated in Section XIII, emerging trends are discussed in Section XIV, and Section XV concludes.

II. RESEARCH METHODOLOGY

To consolidate what is known about AI-enabled smart cities, this study uses a structured narrative literature review together with comparative case analysis. Searches covered peer-reviewed journal articles, official government documents, and publications of international organizations from 2008 to 2025, with keywords such as "artificial intelligence AND smart city," "sustainable urban development AND machine learning," and "smart cities AND Sustainable Development Goals." The material drew on urban informatics, computer science, and sustainable development policy.

Three inclusion criteria guided source selection: (i) a clear account of how an AI or machine learning method is applied in an urban setting, (ii) sufficient detail for comparison, and (iii) a verifiable origin, for example a journal, an institution, or a government policy or program. The case studies were picked to span varied governance systems, income levels, and regions, namely high-income cities in Europe and Asia and, from a developing economy, cities in India. The variety is deliberate, because earlier smart city research has tended to over-represent well-resourced, high-income cities and to neglect low-resource settings, even though the latter are more typical of fast-growing urban areas.

The quantitative indicators in Section VII were taken only from publications of a government body, a city administration, or a peer-reviewed study, and each value is given alongside the kind of source behind it. Where no dependable published value existed, the indicator is flagged as missing and no estimate is offered.

Both the multi-layered conceptual framework of Section V and the SDG mapping of Section IX were built inductively from patterns observed in the literature and not borrowed from an existing theoretical model. As a result, the framework reflects the technical architecture that is commonly used as well as the sustainability goals that the architecture is meant to serve.

Given the practical, cross-disciplinary character of the subject, priority went to works that combine technical detail on the algorithms with the relevant policy context, rather than purely algorithmic papers that ignore urban deployment or purely policy papers that say nothing about technology. The reference list mirrors this balance, drawing on computer science venues, urban studies journals, government documents, and reports from international agencies.

III. LITERATURE REVIEW

A. The Development of the Smart City Concept

Over the past two decades, the meaning of the smart city has shifted considerably. Early work concentrated on technological infrastructure and sensor networks, and Hollands asked whether the "smart city" label reflected genuine urban progress or was chiefly a marketing device [12]. Caragliu et al. tied a city's smartness to investment in human and social capital and to participatory governance across European cities [4]. Albino et al. compared the many definitions in circulation and showed that attention had moved from information and communication technology (ICT) alone toward people, institutions, and sustainability outcomes [3].

With this shift, smart cities came to be seen as socio-technical systems and not merely as engineering projects. According to Nam and Pardo, the success of a smart city initiative depends on three interrelated dimensions: technology, people, and institutions [13]. Chourabi et al. subsequently offered a more detailed integrative framework built on eight critical factors, namely management and organization, technology, governance, policy context, people and communities, economy, built infrastructure, and the natural environment [14].

B. IoT and Big Data as the Infrastructure

Inexpensive sensors and wireless communication standards turned the IoT into the connective tissue of the smart city, gathering data on traffic flow, air quality, energy use, and infrastructure condition. Zheng et al. called this urban computing, meaning the acquisition, integration, and analysis of the large, heterogeneous data that cities generate in order to address urban problems [15]. Kitchin pointed to the promise of big data for planning decisions, yet cautioned against flattening the real-time city into a technocratic reading [16]. Allam and Dhunny contended that big data and AI belong inside urban planning and urban culture and should not be bolted onto cities as separate technical systems [6].

C. The Move towards AI-Enabled Urbanism

Recent scholarship has tackled the convergence of AI and sustainability head-on. Bibri and Krogstie maintained that smart city development cannot be detached from sustainability goals, since otherwise technology may raise, not lower, resource consumption and social inequality [17]. Cugurullo coined the notion of "urban AI" to describe a transition from automation to autonomy, in which cities start to optimize themselves, and he raised early questions about who is responsible for, and who controls, algorithmic decisions at city scale [7]. Ullah et al. surveyed AI and machine learning applications across smart city domains [5], while Yigitcanlar et al. conducted a systematic literature review to pinpoint both the contributions and the risks of AI

in building smarter cities [8]. Looking at global goals, Vinuesa et al. concluded that AI can enable most SDG targets but may hinder others, which makes the way it is deployed decisive [11].

Studies from 2024 and 2025 build further on this work. Alsabt et al. reviewed 51 peer-reviewed papers on AI in smart cities and grouped the findings under four drivers (sustainability, efficiency, connectivity, and citizen engagement), while emphasizing data privacy, algorithmic bias, and inequality as lasting risks [18]. Bibri et al. analyzed 185 studies published from 2019 to 2023 on combining AI, the artificial intelligence of things (AIoT), and urban digital twins for environmental planning; they concluded that integrating these technologies can help with complex environmental problems, though major barriers persist [19]. The same group looked at how AIoT can underpin data-driven environmental governance in eco-cities [20]. Sacoto-Cabrera et al. examined 64 studies on IoT, AI, and digital twins in smart cities and found continuing gaps in interoperability, predictive modeling, data privacy, and impact evaluation [21]. Case-based research points in the same direction: a study of the City Brain in Hangzhou reports better traffic efficiency in pilot corridors and faster emergency response, although its abstract offers only directional findings [22]. Related work on AI in urban planning has identified uses such as land-use prediction and disaster management, while noting that adoption is uneven between high-income and low-income cities [8], [18].

D. Smart City Developments in India and the Global South

A smaller but expanding body of work looks at smart city development in India. Praharaj et al. studied the 100 Smart Cities Mission through the lens of policy integration and offered a critical view of how it approaches urban innovation [23]. In a later study of the 100 Integrated Command and Control Centers (ICCCs) established under the Mission, Praharaj found that platform design and usage vary widely across cities, that city size has a strong bearing on whether ICCCs are adopted and run successfully, that cities give priority to technology-led mobility, surveillance, and utilities over social and environmental sustainability, and that governance arrangements hand private companies more sway over public affairs [24]. Such findings agree with the research gap identified below and motivate the Governance Layer of Section V, which sits alongside the more familiar technical layers.

E. AI Ethics and Governance Literature

A separate but increasingly pertinent body of work considers ethical and governance questions around AI in the public sector. It underlines the need for explainable algorithmic decisions, because public confidence requires at least a basic grasp of how a given decision or recommendation came about [25]. Surveys on bias and fairness demonstrate how models trained on historical data can reproduce and magnify existing inequalities [26], and research on the computational cost of deep learning shows that the energy needed to train large models is far from negligible [9]. For cities, this literature suggests that technical capability is necessary but not enough: adoption also demands institutional frameworks for transparency, appeal, and accountability, themes that return in the challenges of Section VIII.

F. Summary of Selected Related Studies

Table 1 summarizes the focus of the main related studies discussed above.

Table 1: Selected Related Studies on AI-Enabled Smart Cities

Ref.	Year	Focus and scope
[3]	2015	Definitions, dimensions, and initiatives of smart cities
[7]	2020	Urban AI: from automation to autonomy; accountability questions
[8]	2020	Systematic review of contributions and risks of AI in smarter cities
[11]	2020	AI as an enabler or inhibitor of the SDGs
[13]	2011	Technology, people, and institutions as the three smart city dimensions
[16]	2014	Critical analysis of big data and the real-time city
[18]	2024	Review of 51 papers (2022–2023); four drivers; conceptual model
[19]	2024	Review of 185 studies on AI, AIoT, and digital twins for environmental planning
[21]	2025	Review of 64 studies on IoT, AI, and digital twins; gaps in interoperability and impact evaluation
[24]	2025	Analysis of 100 ICCCs in India's Smart Cities Mission

G. Research Gap

Taken together, the reviewed literature supports three findings that motivate this paper. The first is that smart city development has moved from an infrastructure-centered paradigm to one based on data and intelligence. The second is that sustainability tends to be treated as an afterthought although it lies at the heart of the global policy agenda. The third is a need to consolidate frameworks that identify particular types of AI technology and their effect on urban sustainability, that make governance an explicit architectural component, and that use measurable indicators to compare high-income and developing economies. Recent reviews [18], [19], [21] point to gaps in impact evaluation and interoperability, and the study of India's command centers [24] indicates that governance capacity sets a ceiling on what technology can deliver. This paper responds to these gaps by developing a five-layer model, comparing selected cities on qualitative and quantitative criteria, and mapping AI applications to the SDGs.

IV. AI TECHNOLOGIES ENABLING SMART CITIES

This section surveys the families of AI techniques that appear most often in urban settings, moving from the best established to the more experimental. For each, the subsection notes the layer of the Section V framework to which the technique corresponds most closely.

A. Machine Learning for Predictive Urban Analytics

Machine learning models are used extensively to forecast demand for electricity, water, and transport capacity from

past consumption, weather conditions, and demographic data [5], [15]. With such forecasts, city management can shift from a reactive stance to proactive, and even prescriptive, resource management, cutting resource waste and service interruptions. Ensemble and gradient boosting models are particularly common in municipal deployments since they achieve high prediction accuracy at a much lower computational cost than deep neural networks. (Intelligence Layer)

B. Computer Vision for Traffic and Public Safety

Computer vision algorithms analyze video streams from traffic cameras and public spaces in order to spot congestion and accidents, estimate pedestrian density, and drive adaptive traffic signaling. They are also applied to automated incident detection in public safety, although this raises the surveillance and privacy concerns taken up in Section VIII. Convolutional neural networks are still the leading technique for detecting and classifying objects in these deployments, and inference is increasingly carried out at the edge. (Intelligence Layer)

C. Natural Language Processing for Citizen Engagement

Natural language processing (NLP) powers multilingual chatbots for citizen services that accept requests, log complaints, and settle grievances in routine cases without involving staff. Sentiment analysis of social media and civic platforms likewise lets city authorities gauge public opinion on infrastructure changes and policies. (Application Layer)

D. IoT-AI Integration for Real-Time Monitoring

Pairing IoT sensor networks with edge and cloud-based AI models makes real-time monitoring possible for air and water quality, the condition of bridges and buildings, and the stability of the energy grid. Because edge AI cuts the bandwidth and latency costs of sending raw data to central servers, it is especially valuable where backhaul capacity is scarce. (Sensing and Data Layers)

E. Digital Twins and Simulations

A digital twin joins a 3D city model with AI-enabled simulation, allowing planners to test the effects of interventions such as a new transport route or re-zoning before putting them into practice, and at lower cost [19], [21]. Simulations that vary climatic and demographic parameters can also be used to study flooding and heat-wave scenarios as the climate becomes less stable. (Intelligence Layer)

F. Reinforcement Learning for Adaptive Control

Reinforcement learning (RL) is an AI technique for sequential decision making that is finding growing use in traffic signal control, electricity pricing, and building management. Unlike supervised learning, RL agents learn optimal policies by interacting with a simulated or real environment, so they suit applications in which the best configuration keeps changing. As an illustration, Wei et al. trained an RL agent on real traffic data to control signal phases and reported shorter travel times than conventional control methods [27]. (Intelligence Layer)

G. Explainable and Generative AI for Governance

Decisions that directly affect citizens, such as issuing permits and allocating resources, are increasingly shaped by AI systems. Explainable AI (XAI) comprises methods that make model outputs intelligible to public officials and to citizens who lack technical expertise [25]. Generative AI models can assist designers in producing zoning and infrastructure options during early urban design, and automated systems can then evaluate those options; even so, the technology is still at an early research stage and has some way to go before gaining mainstream acceptance. (Application and Governance Layers)

H. Federated Learning for Privacy-Preserving Urban AI

With federated learning, several municipal departments and cities can build a shared AI model by training on their local data, without sending citizen information to a central database [28]. What is exchanged between systems are model updates in the form of gradient values, while the underlying data stay on local servers controlled by the department that gathered them. This makes the method well suited to urban applications with data-protection needs, since departments can develop shared public-benefit models and still keep independent control over their own data. (Data and Intelligence Layers)

V. PROPOSED CONCEPTUAL FRAMEWORK

A. Five Layers and Their Interaction

To bring the technologies described above together into one coherent system for AI-powered smart cities, this paper proposes a five-layer conceptual framework. Its layers are Sensing, Data, Intelligence, Application, and Governance, as summarized in Table 2 and Figure 1. The first four form the technical stack that is typical of IoT-based smart city architectures, and the fifth, the Governance Layer, is the addition made here. Any mention of the "framework" in this paper covers all five layers.

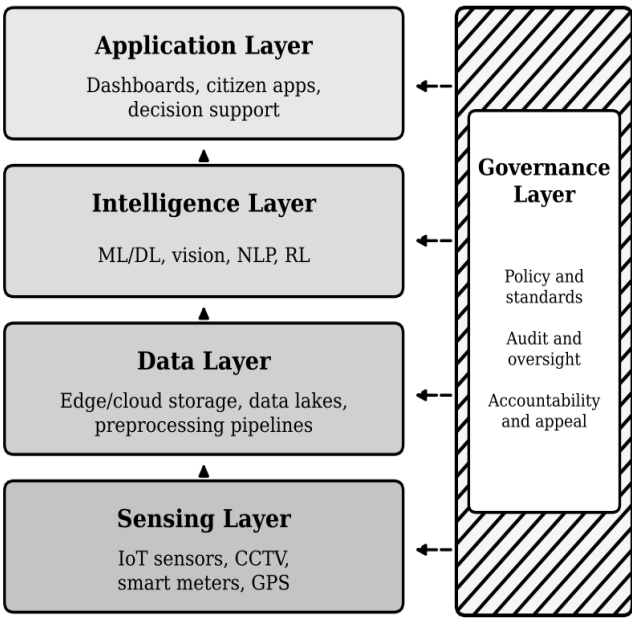

Figure 1: Five-layer framework for AI-powered smart cities. Solid arrows show data flow through the technical stack; dashed arrows show oversight exerted by the Governance Layer on every layer

Table 2: Layered Framework for Ai-Powered Smart Cities

Layer	Core Components	Representative Function
Sensing	IoT sensors, closed-circuit television (CCTV), smart meters, GPS	Continuous capture of environmental and infrastructure data
Data	Edge/cloud storage, data lakes, preprocessing pipelines	Cleaning, integration, and storage of heterogeneous urban data
Intelligence	Machine learning and deep learning (ML/DL) models, computer vision, natural language processing, reinforcement learning engines	Pattern recognition, forecasting, and adaptive control
Application	Dashboards, citizen apps, decision-support tools	Actionable insight delivery to citizens and administrators
Governance (fifth, cross-cutting)	Policy frameworks, data standards, audit and accountability bodies	Oversight of all four layers: standard-setting, audit, accountability, and feedback

In the Intelligence Layer, the AI techniques of Section IV produce forecasts, classifications, and recommendations. The Application Layer converts these outputs into operational interfaces that city officials, utility operators, and residents can use directly.

B. Role of the Governance Layer (Fifth Layer)

The Governance Layer is different in kind from the other four. Sensing, Data, Intelligence, and Application form a pipeline along which data move upward and decisions return to the physical city. Governance does not handle data within this pipeline; instead it constrains, audits, and legitimizes every layer in it, through four functions. The first is standard-setting, which covers data-sharing rules, open data and API requirements, and procurement conditions for the Sensing and Data layers. The second is oversight, in the form of independent audits of the Intelligence Layer for bias, privacy protection, and cybersecurity. The third is accountability at the Application Layer, secured through appeal procedures, human override of automated recommendations, and documentation of decisions. The fourth is closing the feedback loop by gathering key performance indicators (KPIs) and sustainability reports (Section X) that influence procurement and deployment choices in the lower layers.

The case for treating governance as its own layer, and not as a property of the other layers, rests on empirical evidence. A study of India's command and control centers found that cities favored technology-led mobility, surveillance, and utilities and that governance models and city capacity had a strong influence on outcomes [24], and the ethics literature shows that public trust hinges on explainability, transparency, and the chance to appeal [25]. The framework therefore works as a feedback system: Governance Layer decisions shape what is deployed at the Application Layer and which data are collected at the Sensing Layer, and the resulting data patterns in turn steer the continued development of the AI systems. Earlier descriptions of the framework that list only the Sensing, Data, Intelligence, and Application layers refer to the technical stack alone.

C. Worked Example: Adaptive Traffic Signal Control

An example from practice shows how the five layers work together. At the Sensing Layer, roadside cameras and inductive loop detectors collect vehicle counts and speeds. The Data Layer cleans these readings and aligns them with weather information and calendar records. Using the combined data, the Intelligence Layer generates short-term traffic predictions and derives signal-timing recommendations through reinforcement learning, as described in Section IV-F. The Application Layer passes the adjustments on to signal controllers and gives traffic control rooms a live picture of congestion. The Governance Layer lays down the procedure that officers follow when AI recommendations clash with their own judgment in the field, and it specifies the documentation required to review disputed decisions later. Running the Intelligence Layer without a Governance Layer would bring about the accountability problems explained in Section VIII.

VI. APPLICATION DOMAINS AND CASE STUDIES

Following the selection criteria of Section II, this section looks at how the AI techniques of Section IV have been put into practice under different economic conditions and deployment approaches.

A. Smart Transportation and Mobility

Singapore runs AI-based traffic signal systems that use real-time data to adjust operations, improving traffic flow, reducing vehicle pollution, and shortening travel times. Its public transit system relies on predictive maintenance models that schedule work ahead of equipment failure, which keeps service quality up. The city-state further pairs autonomous vehicle testing with AI-based, demand-responsive scheduling of public transport, an example of an advanced approach to AI mobility management.

B. Smart Energy Management

Amsterdam's smart grid uses AI-based demand forecasting to match renewable power generation with the naturally fluctuating electricity demand of households and businesses, and to keep fossil-fuel plants running as little as possible. India's Smart Cities Mission operates demand-response systems in selected urban areas to ease peak-load pressure on municipal power systems, although these programs are smaller in scale than their European counterparts, which benefit from more advanced grid digitalization. In Barcelona, sensor-based smart lighting is reported to have reduced public lighting energy use by about 30 percent [29].

C. Smart Waste and Water Management

In Barcelona, waste bins fitted with fill-level sensors are served by route-optimization software that cuts the number of collections runs and so lowers fuel and operating costs. For water management, AI-based acoustic and pressure-sensor systems have become standard practice for detecting

pipeline leaks early, helping to reduce the non-revenue water losses that continue to plague growing cities across South and Southeast Asia. Barcelona's sensor-based park irrigation is reported to have raised water conservation by 25 percent [29], and Singapore reports a water loss rate of 7.2 percent in its national distribution system in 2025, which the national government describes as among the lowest in the world [30].

D. Songdo and Purpose-Built Smart Cities

In South Korea, Songdo International Business District was designed from the outset with digital infrastructure, including sensor networks and automated waste collection. This approach links sensing and intelligence systems more closely, but it also exposes the heavy expense and long construction periods of purpose-built smart cities, compared with the step-by-step upgrading followed by most cities, Indian cities included.

E. India's Smart Cities Mission

Since its launch in 2015, India's Smart Cities Mission has set up Integrated Command and Control Centers (ICCCs) in 100 cities that merge traffic, utility, and public safety data into single dashboard systems [24]. The smart city centers in Pune and Bhubaneswar run AI-based video analytics with two main uses: spotting traffic violations and managing crowds during public festivals. Pune's municipal corporation has also reported that its adaptive traffic system, installed at 125 intersections, cut congestion by 15 percent and raised average vehicle speed by 10 percent [31].

F. Additional Global Perspectives

The cases above do not capture all of the useful variation among cities. Copenhagen has linked AI analytics for cycling and pedestrian movement to its sustainable mobility plan, and an evaluation of its “green wave” signal coordination for cyclists found a 17 percent cut in travel time on one corridor [32]. Hangzhou's City Brain applies AI to traffic management and is reported to have improved efficiency in pilot corridors and shortened emergency response times [22]. Dubai has set up an AI-based governance system in which machine learning ranks services across municipal departments, overseen by a dedicated government AI office. Shenzhen operates a very large computer vision and IoT system for traffic and public safety at a scale that few cities can match, and that scale has drawn privacy concerns worldwide. Viewed alongside Sections VI-A to VI-E, these cases show that AI-based smart city strategies emerge from a mix of local government objectives, security requirements, and the technological components that are actually available.

The case studies span a range from citywide integrated systems in Songdo's purpose-built environment to the department-by-department retrofitting that is standard under India's Smart Cities Mission. These contrasting deployment models were chosen on purpose, so that patterns shared by all implementation approaches can be examined instead of patterns that stem from basic differences between cities.

VII. COMPARATIVE ANALYSIS OF SMART CITY INITIATIVES

A. Qualitative Comparison

Table 3 summarizes the case studies of Section VI by deployment model and principal constraint. Affluent cities such as Singapore and Amsterdam enjoy established digital systems and uncomplicated governance rules, whereas India meets many obstacles in rolling out its Smart Cities Mission because of aging infrastructure, data control scattered across city departments, and scarce financial resources for technology [24].

Table 3: Comparative Analysis of Selected Smart City Initiatives

City / Program	Deployment Model	Principal Constraint
Singapore	Retrofit, high resource	High initial capital cost
Amsterdam	Retrofit, high resource	Grid modernization pace
Barcelona	Retrofit, moderate resource	Vendor interoperability
Songdo (S. Korea)	Purpose-built	High cost, long timeline
India (Smart Cities Mission)	Retrofit, constrained resource	Legacy infrastructure, data fragmentation

No single deployment model is the ideal answer in every situation. Building Songdo as a dedicated urban zone made for tighter technical integration, but it cost more money and time than most existing cities can afford. Retrofit-based approaches, which India and most other cities worldwide follow, should concentrate funding on the Data and Governance layers of the Section V framework, since these layers deal with the fragmented systems left over from older infrastructure.

Table 3 also indicates that how fast a deployment moves past its pilot phase depends more on governance arrangements than on technological progress. In Singapore and Amsterdam, infrastructure choices are under centralized municipal control, so a successful pilot can be scaled citywide quickly. India's Smart Cities Mission, by contrast, works through many independent municipal corporations, each with its own procurement procedures and level of technical expertise. A pilot that succeeds in Pune therefore does not readily translate into adoption elsewhere. This lends support to the recommendation in Section XII for unified data standards and shared audit systems that travel with the technology, in place of separate approval processes in each city.

B. Measurable Indicators

A qualitative comparison by itself cannot reveal whether a deployment yielded sustainability gains. For that reason, Table 4 gathers the measurable indicators for energy, traffic, and water that could be located in published sources. The values appear exactly as published and should be read with three cautions in mind. First, most were reported by the city or program itself and have not been independently verified. Second, baselines, periods, and spatial scopes differ, so the values cannot be ranked against each other. Third, the sources do not always credit the result to AI specifically, as distinct from wider digital or operational improvements.

Table 4: Measurable Indicators Reported For Selected Initiatives

City / Program	Indicator	Reported value	Source type
Barcelona	Energy: public lighting	About 30% energy saving	City report [29]
Barcelona	Water: park irrigation	25% more water conserved (about US$555,000 per year); 68% of parks	City report [29]
Singapore	Water: system loss rate	7.2% loss rate in 2025	Government reply to Parliament [30]
Copenhagen	Traffic: cyclist travel time	17% shorter on one corridor; stops from six to under one	City evaluation, as cited in [32]
Pune	Traffic: congestion and speed	15% less congestion; 10% higher average speed (125 junctions)	Municipal corporation, via press [31]
Agartala	Traffic: peak throughput	30% higher (22 junctions)	Curated, not validated [33]
Tumakuru	Traffic: congestion incidents	25% fewer at intelligent traffic management system (ITMS) junctions	Curated, not validated [33]
Hyderabad	Traffic: peak travel time	12% shorter	Curated, not validated [33]

The values in Table 4 suggest that AI-assisted traffic management can improve local operational metrics by roughly 10 to 30 percent, that sensor-driven irrigation and lighting can achieve double-digit resource savings, and that Singapore's national water loss rate is low by international standards. They do not establish that such gains carry over beyond the junctions, corridors, or sub-systems in which they were measured. A number of the figures in Table 4 come from a government-hosted collection of submissions that, by its publisher's own statement, is not independently validated [33], and the Pune figures originate in a municipal announcement relayed by the press [31].

Table 5: Availability of Reliable Indicator Data by Category

Category	Evidence found in this review	Status
Energy savings	Public lighting, Barcelona [29]	Limited; city-reported
Emission reduction	No, independently verified city-level figure found	Gap
Traffic efficiency	Copenhagen, Pune, and three Indian cities	Best covered; local scope
Water conservation	Barcelona irrigation; Singapore loss rate	Limited; no common baseline
Waste management	No, independently verified city-level figure found	Gap

Table 5 makes clear where the evidence is weak. Traffic efficiency is the category with the best documentation. Emission reductions are generally inferred from traffic or energy gains and not measured directly, and the sources reviewed contained no verified waste-management performance figures, so none are estimated here. The gap is a finding in its own right: it backs the call in Section X for shared, audited indicators with stated baselines. Reported gains should also be weighed against the energy and water consumed by AI infrastructure [9], because a city that saves energy on its roads but adds energy-intensive computing may see no net sustainability benefit.

VIII. CHALLENGES AND ETHICAL CONSIDERATIONS

Nothing in the technologies and case studies above shows that deploying AI in cities yields positive results at every stage. The ten challenges in this section are risks that surfaced repeatedly in the deployment assessments of Sections VI and VII and in the literature [8], [18], [21]. They explain why the Governance Layer introduced in Section V is a core element of the framework and not an optional extra on top of the technical stack.

A. Data Privacy and Surveillance

The large number of cameras and sensors in public areas gives rise to legitimate fears of mass surveillance that endangers citizens' personal privacy. Safeguarding urban AI systems calls for firm data governance rules, collection of data only for stated purposes, and anonymization to block unauthorized access, since video analytics systems that started out as traffic control tools can end up tracking entire populations without public consent [24].

B. Algorithmic Bias and Fairness

When AI models learn from historical urban data, they take on the social prejudices embedded in it, and they may go on reinforcing the biases that society already faces [26]. A system trained on police records, for instance, may keep sending excessive police presence to areas with historically high recorded crime while under-serving communities where recorded crime is low because reporting is weaker. Organizations should carry out regular fairness audits and build in safeguards against these risks, and the bodies conducting the audits must stay independent of the vendors who supply the AI systems.

C. Digital Divide and Inclusivity

Smart city applications that rely on smartphone ownership and digital skills risk shutting out elderly people, low-income residents, and rural migrants from AI-based services. Any move to AI therefore requires organizations

to retain non-digital service channels and to follow inclusive design principles, as these services stay essential in developing economies where smartphone and broadband access is incomplete.

D. Interoperability and Standardization

Because vendors and city departments do not share standardized data formats, systems end up isolated, which blocks data sharing and the cross-domain learning that AI relies on [21]. Open data standards and API-based integration can lessen this fragmentation, but they are difficult to enforce once multi-vendor contracts have been signed.

E. Environmental and Energy Cost of AI Infrastructure

Large-scale AI models need data centers for training and operation, and these consume large amounts of energy and cooling water [9]. Smart cities need strategies for measuring their own environmental impact and should not assume that adopting AI automatically advances sustainability targets. When accuracy is comparable, small models running at the edge should be preferred to large models running centrally.

F. Cybersecurity Risks

Interconnecting urban systems widens the attack surface and allows cyber threats to propagate across systems, so a breach in one sensor network or control system could take down essential services such as traffic management and electrical power distribution. Because automated, networked systems now control many vital operations, AI-based urban infrastructure must have cybersecurity designed in from the start.

G. Cost, Scalability, and Vendor Lock-In

Pilots of AI-based smart city systems often run on vendor platforms that tie cities to a single supplier, making it hard to change providers or extend projects across the whole city. Procurement rules that demand open standards and data portability from the first contract lower this risk, yet retrofitting such rules into existing agreements is very hard.

H. Legal and Regulatory Gaps

In many fast-growing urban areas, legal frameworks for AI in public administration are incomplete, as current rules do not adequately cover these systems. This regulatory vacuum leaves institutions exposed whenever AI systems go live before suitable monitoring capacity is in place.

I. Public Trust and Institutional Acceptance

If citizens and municipal staff decline to rely on AI, it cannot produce sustainability benefits. People distrust automated systems that are unable to explain their decisions [25], and earlier bad experiences with digital government services, which have nothing to do with smart cities, deepen that distrust. Some also suspect that automated decision systems benefit officials more than citizens. Institutional acceptance can be built through continuing public outreach, set procedures for contesting automated decisions, and early, visible service improvements before more complex AI systems are introduced.

J. Workforce Skills Gap

In many municipal governments, there are too few staff with the data science and machine learning knowledge needed to build and maintain AI systems without leaning on vendors, and this weakens both procurement and the ability to monitor system performance in operation. Addressing the gap takes sustained funding for training city employees, partnerships with universities, and public-sector data careers that can compete with private-sector positions.

IX. DISCUSSION: ALIGNING AI-POWERED SMART CITIES WITH THE SDGS

The applications covered in this paper line up directly with several United Nations Sustainable Development Goals, as Table 6 summarizes [10], [11]. With this mapping, planners and policymakers can judge AI spending by its sustainability impact and not by conventional efficiency metrics.

Table 6: Mapping Of Ai-Powered Smart City Applications To Selected SDGS

SDG	Relevant AI Application
SDG 3 – Good Health and Well-Being	AI-based air and water quality monitoring and early-warning systems
SDG 6 – Clean Water and Sanitation	Leak detection and AI-optimized water distribution
SDG 7 – Affordable and Clean Energy	AI-based demand forecasting and renewable grid balancing
SDG 9 – Industry, Innovation and Infrastructure	Predictive maintenance and digital twin simulation
SDG 11 – Sustainable Cities and Communities	Smart transportation, waste management, and e-governance
SDG 13 – Climate Action	Emission reduction via traffic optimization and energy efficiency

The mapping indicates that smart cities should judge the value of AI through whole-system assessment. A traffic optimization system can advance two SDGs by improving urban transport and reducing vehicle pollution, but its net benefit hinges on how well it accounts for the environmental cost of its own AI infrastructure, as discussed in Section VIII. Under SDG 3, an AI-based air quality monitoring system yields public health benefits only if its data are turned into enforcement action through the Governance Layer of Section V, and not left as a passive dashboard metric. Future strategies should accordingly rest on sustainability assessments that cover full life-cycle impacts and not just the operational performance of AI systems.

Every mapping in Table 6 also calls for its own implementation strategy. Under SDG 3, the Intelligence Layer has to get air and water quality alerts to public health agencies quickly, rather than leaving the warnings on technical dashboards. Under SDG 6, the main obstacle is the state of pipe networks that are decades old and pre-date digital monitoring. Under SDG 7, the granularity and real-time availability of grid data limit progress more than the sophistication of any forecasting model. Under SDG 9, advancement depends on how mature urban digital twin simulation is, and this is among the costliest elements of smart city initiatives. SDG 11 gives local citizens the most visible results through better transport, waste management, and e-government services, but those results are exposed to

the digital divide and accessibility problems covered in Section VIII-C. Reaching SDG 13 demands that AI-driven efficiency gains translate into real emission reductions and do not trigger new demand that cancels out the environmental benefits.

Every application discussed here also relies, directly or indirectly, on SDG 17, which calls for stronger partnerships for sustainable development. No municipality can manage all aspects of AI deployment inside its own departments, so outside support is needed. In India, national-level activities are coordinated by the Ministry of Housing and Urban Affairs. For this reason, the financing and operational delivery of AI-based smart city initiatives depend on SDG 17 as a core enabling goal for all the rest.

X. KEY PERFORMANCE INDICATORS FOR EVALUATING AI-POWERED SMART CITIES

As the gaps in Table 5 show, the case studies of Sections VI and VII have no common measurement systems for establishing whether AI-based smart city systems deliver sustainable results. Table 7 offers a compact set of indicators that municipal authorities should track to follow technical operations and environmental impact across the layers of the framework. The indicators complement the SDG-level mapping of Section IX by supplying quantifiable measures that cities can report on a regular quarterly or yearly basis.

Table 7: Proposed KPIs For Ai-Powered Smart City Evaluation

Layer	Illustrative KPI
Sensing	Sensor uptime rate; data completeness percentage
Data	Cross-department data integration coverage
Intelligence	Model prediction accuracy; retraining frequency
Application	Citizen service response time; adoption rate
Governance	Number of independent AI audits conducted per year; share of KPIs published with stated baselines

Tracking KPIs at every layer lets organizations identify which deployment components are behind performance problems. A smart traffic system, for example, may post strong model prediction results while its companion mobile app fails to win citizen adoption; this signals a problem in the Application Layer and not in the Intelligence Layer. A single overall success metric would lack the detail to locate such a problem and to justify targeted funding. Cities that started sharing KPI data, even by basic methods, report that doing so helps them sustain funding for data integration. That integration still needs funding even when it yields no directly visible results, because all the higher layers are built on it.

XI. STAKEHOLDER ROLES AND RESPONSIBILITIES

Four groups of stakeholders must coordinate if the sustainability results described above are to be achieved. Municipal governments carry primary responsibility for the Governance Layer: they need to set data-sharing rules, authorize third-party assessments, and create mechanisms through which people can challenge AI-based decisions. Technology vendors are chiefly responsible for the Sensing, Data, and Intelligence layers, and they should uphold open data standards and supply basic information on the training data and evaluation methods of the models they deploy.

Power distribution companies and water boards control the operational data at the point where the Data and Application layers meet, since they provide vital operating information and need AI recommendations for day-to-day operations. The fourth group consists of citizens and civil society organizations, on whom the Governance Layer relies to evaluate deployed systems, take part in public consultation, and challenge unjust decisions when necessary. Smart city programs that devote specific resources and operational systems to this group, instead of treating citizen participation as secondary, achieve better implementation results and face fewer problems with public confidence, as noted in Section VIII-I.

XII. POLICY RECOMMENDATIONS

Five policy recommendations for municipal governments building AI-based smart city initiatives follow from the comparative analysis and the challenges discussed. First, open data standards should be made mandatory in every AI procurement agreement, so as to prevent vendor dependency and to permit future data exchange among city departments. Second, cities should establish an independent municipal AI audit function that regularly assesses deployed systems for bias, privacy protection, and cybersecurity. This function should be independent of the vendors that built or run the systems and should ground its evaluations in the KPI framework of Section X.

Third, citizen-facing AI applications should go through digital-divide impact assessments before becoming operational, and essential services should retain non-digital options for grievance redressal and utility billing. Fourth, cities should disclose the resource consumption of their AI systems in sustainability reports, next to the operational improvements those systems deliver, and should base later funding decisions on overall environmental sustainability impact and not on operational performance alone.

Fifth, municipal authorities should establish and fund a specialized unit for data governance and AI system monitoring. The unit needs a budget of its own, as its staff must bring together technical knowledge and policy expertise. Vendors, for their part, should be required to show how efficient their systems are and that they can share data across department boundaries. Developing this capability early costs less than retrofitting surveillance systems once a large AI system is already running across the entire city.

XIII. LIMITATIONS OF THE STUDY

Readers should bear in mind several limitations of this review when judging its results. The case studies of Sections VI and VII show different deployment models, but they were not drawn from an exhaustive worldwide selection of all known smart city implementations. Nor do they represent typical small towns, since such places lack complete development documentation.

Secondary sources, mainly published academic work and accessible official government records, form the basis of this paper, and no original data were collected through interviews with city officials or assessments of system performance. The quantitative indicators in Table 4 are for the most part self-reported by the cities or programs concerned, use different baselines and scopes, and have not been independently verified, and no dependable values were found for emission reduction or waste-management performance (Table 5). The KPI framework of Section X is a proposed evaluation system that must still be validated in future research across different urban areas. Even so, through its consolidated framework, comparative analysis, and SDG mapping, the paper gives researchers and municipal staff working on AI-based smart city projects a structured place to start.

XIV. EMERGING TRENDS AND FUTURE DIRECTIONS

A. Next-Generation Connectivity and Ambient Sensing

High-speed, low-latency wireless networks will allow cities to extend urban sensing, as they support better data collection and real-time response at street level for air quality monitoring, noise detection, and pedestrian tracking. The Intelligence Layer of Section V requires fine-grained information to find specific problems, such as faulty traffic signals and individual pollution sources, that go unnoticed in coarser district-level data sets.

B. AI for Circular Economy and Resource Recovery

A newer application in the circular economy pairs computer vision with optimization algorithms to automate the sorting of recyclables at municipal facilities and to match construction materials between demolition sites and new building projects. It is currently deployed on a smaller scale than the transport and energy systems of Section VI, yet it directly supports SDG 12 on responsible consumption and production, and it will likely draw more scientific and political attention as cities pursue more ambitious waste-reduction targets.

C. Climate-Resilient Infrastructure Planning

As severe weather events become more frequent, AI simulation systems are being used to stress-test urban infrastructure for resistance to floods and heat waves [19]. Investors can then steer funds toward infrastructure that is likely to fail under future climate change, and not toward repairing damaged structures after the fact. The move from emergency-driven funding to strategic planning with AI prediction models is a significant development that supports the climate adaptation objectives of SDG 13.

D. Human-AI Collaborative Governance

Human-AI teamwork is the favored practice in urban decision-making at present: AI systems sort recommendations, flag unusual patterns, and lay out competing options, while human officials retain control over vital decisions such as emergency resource allocation. The public sector is likely to keep using the "human-in-the-loop" design pattern as its main approach to AI deployment, because the pattern meets the accountability and legal responsibility requirements set out in Section VIII-H.

XV. CONCLUSION AND FUTURE SCOPE

This paper has studied AI as a foundational technology for sustainable smart cities. It reviewed the essential enabling methods, proposed a five-layer conceptual framework (Sensing, Data, Intelligence, Application, and Governance), assessed global and Indian smart city programs using qualitative and measurable criteria, and aligned specific applications with the United Nations SDGs. AI is able to improve urban resource management, service operations, and resilience. The indicators reported, for example improvements of roughly 10 to 30 percent in local traffic metrics and double-digit savings in water and lighting, are promising, but they are largely self-reported, limited in scope, and missing for emissions and waste. To realize the benefits, deliberate planning is needed in the form of data management systems, environmental protection standards, equal treatment protocols, inclusive design, and compatible technology platforms, and this is the role of the Governance Layer.

Future research should develop privacy-preserving approaches, federated learning among them, that allow cities to build AI models across distributed municipal data systems without exposing sensitive citizen information. Improved explainable AI (XAI) systems are also required, so that citizens and officials can understand automated urban decisions and keep the ability to challenge them. Longitudinal studies that follow the sustainability outcomes of AI-based smart city projects over several years would help show which projects have lasting effects and which are merely temporary demonstrations. Further work should connect AI-based smart city efforts to existing sustainability assessment systems built on SDG indicators, so that funding decisions follow sustainability goals and not novelty for its own sake, and it should gather independently verified emission and waste-management indicators.

Sustainable cities cannot be achieved through smart technology alone; institutions must take the lead and not depend on technological solutions by themselves. Through its layered framework, comparative analysis, and policy recommendations, this paper gives researchers, students, and municipal practitioners a starting point, with the aim of directing the power of AI toward sustainable urban development.

CONFLICTS OF INTEREST

The authors declare that they have no conflicts of interest.

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