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Artificial Intelligence in Smart Cities: Accelerating Urban Sustainability through Intelligent Systems

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Abstract

The rapid urbanization of the 21st century has intensified the need for cities to become more resilient, efficient, and sustainable. Artificial Intelligence (AI) offers transformative potential in this context by enabling real-time data-driven decision-making, predictive modeling, and autonomous system control across diverse urban domains. This review explores the integration of AI technologies into smart city infrastructures with a focus on enhancing urban sustainability. It critically examines AI applications in energy-efficient building systems, intelligent transportation networks, air quality monitoring, waste management, and urban planning. Drawing from interdisciplinary literature and case studies, the review highlights how AI contributes to reducing emissions, optimizing resource allocation, and improving public services. While AI presents significant opportunities for systemic sustainability gains, the paper also underscores key challenges including data governance, algorithmic bias, energy consumption of AI systems, and the risk of technological exclusion. The findings emphasize the necessity of aligning AI deployment with inclusive governance models, ethical standards, and sustainable development goals. A strategic roadmap is proposed to guide future research and policy, emphasizing the importance of equitable data infrastructures, cross-sectoral partnerships, and transparent AI model design. This review contributes to a deeper understanding of how intelligent systems can be leveraged to address complex urban sustainability challenges in an era of environmental uncertainty.

Keywords: Artificial Intelligence; Smart Cities; Urban Sustainability; Intelligent Infrastructure; Resource Optimization; Environmental Monitoring

1. Introduction

1.1. Urbanization, Climate Pressure, and the Need for Smart Cities

Rapid urbanization and escalating climate pressures are driving the adoption of smarter, more sustainable urban infrastructure models. At the nexus of urban development, environmental stewardship, and digital innovation, Artificial Intelligence (AI) emerges as a transformative force in designing future-ready cities. This review examines the role of AI technologies, particularly when integrated with the Internet of Things (IoT) and urban digital twins, in enhancing

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resource efficiency, environmental monitoring, and governance within urban systems. We explore applications across energy optimization, mobility, waste management, air quality, and urban planning, while proposing a roadmap for ethical, inclusive, and sustainable smart city governance.

Global urbanization is accelerating, with over half of the world's population now residing in urban centers, which account for approximately 70% of global greenhouse gas emissions. This rapid urban growth intensifies challenges such as infrastructure strain, air pollution, and rising temperatures, exposing the limitations of traditional governance models. The need for smart city solutions capable of addressing interconnected challenges in climate resilience, mobility, and energy efficiency is increasingly evident. Environmentally sustainable urban ecosystems, often termed "eco-cities," leverage AI, IoT, and big data to foster resilient and livable urban environments. Through real-time data collection and analytics, these systems enable dynamic adaptation, operational optimization, and strategic long-term planning. However, barriers such as fragmented datasets, delayed governance responses, and unequal digital access continue to impede widespread technology deployment, underscoring the need to reposition cities as critical platforms for transformative climate action.

An integrated AI–IoT framework offers a paradigm shift from reactive to anticipatory, data-informed decision-making. AI-powered digital twins, implemented in cities such as Las Vegas and Barcelona, exemplify how data-driven simulation and scenario planning enhance sustainability performance. By modeling infrastructure, climate impacts, and behavioral patterns, these tools enable urban managers to test interventions prior to implementation, minimizing risks and optimizing efficiency. With the global urban population projected to increase by over 2.5 billion by 2050, the urgency to embed AI into smart city strategies is paramount. Such approaches are essential for reducing environmental footprints, strengthening disaster resilience, and ensuring a high quality of life in urban environments navigating unprecedented change [1-4].

1.2. Why AI Is Essential for Urban Sustainability

AI is uniquely equipped to address the complexity, dynamism, and interconnectedness of urban systems by enabling real-time optimization, predictive analytics, and automation across multiple domains. In energy systems, AI-driven algorithms enhance load forecasting, demand response, and the integration of distributed renewable energy resources, which are vital for smart grid performance and urban energy resilience. Advanced machine learning techniques, such as neural networks, random forests, and ensemble methods, are employed to predict energy demand, detect water leaks, and optimize infrastructure within built environments, contributing to operational efficiency and resource conservation [5-6].

In waste management, the integration of AI with IoT sensors streamlines collection processes by optimizing routes, monitoring fill levels in real time, and automating waste stream classification for recycling or disposal. These systems enhance operational efficiency and support zero-waste strategies and circular economy goals through predictive waste generation modeling and automated sorting. AI's transformative potential extends to urban planning through the use of digital twins and advanced simulation tools that model complex urban dynamics, including land use, mobility trends, climate exposure, and resource flows. By integrating generative AI into digital twin platforms, cities can autonomously generate urban datasets and simulate multiple future scenarios, enabling sustainable design and evidence-based policy testing. Cities like Barcelona and Singapore demonstrate the practical application of these technologies, leveraging digital twins to plan for 15-minute city concepts and integrate green infrastructure, ensuring equitable and efficient urban development. By combining predictive intelligence with high-fidelity modeling, AI empowers urban planners and policymakers to design interventions that are adaptive to current challenges and resilient to future uncertainties [5,7].

1.3. Scope and Objectives of the Review

This review presents a multidisciplinary synthesis of AI-driven approaches to urban sustainability governance, structured around five core domains: energy systems, mobility, waste management, environmental monitoring, and urban planning. Its objectives are to examine key AI applications in smart urban contexts, including smart grids, traffic flow optimization, HVAC automation, waste processing, air-quality monitoring, and digital twin modeling; to analyze enabling technologies and infrastructure such as AIoT integration, data interoperability frameworks, and the use of generative AI in urban digital twins; and to identify critical challenges and governance considerations, including algorithmic biases, privacy concerns, the energy demands of AI, and inequities in digital access, while proposing a strategic roadmap informed by both literature and real-world implementations. The discussion draws on a broad evidence base of peer-reviewed research, systematic reviews, white papers, and institutional reports published over the past five years.

Table 1 Overview of Key AI Applications Across Smart City Domains

Domain	AI Application	Enabling Technologies	Key Benefits	Challenges	Real-World Examples/Cities
Energy Systems	Smart Grids and Demand Response	Machine Learning (e.g., Neural Networks), IoT Sensors	Real-time optimization, 7-20% load reduction, reduced emissions	Data quality issues, integration with renewables	China (load reductions in commercial sectors)
Energy Systems	Predictive Maintenance in Buildings	Deep Learning, Edge Computing	25% energy cost savings, carbon emission reductions	Sparse datasets in older buildings	Global deployments in thousands of buildings
Energy Systems	Renewable Energy Integration	Predictive Modeling, Microgrids	Accurate solar forecasting, reduced grid strain	Variability in renewable outputs	Urban microgrids with solar PV and EV charging
Mobility	Intelligent Traffic Management	Real-time Data Analytics, CCTV Feeds	25% travel time reduction, 10% emission decrease	Policy gaps and enforcement	Sydney (adaptive signals), Seattle, Hamburg
Mobility	Public Transportation Optimization	LSTM Networks, Reinforcement Learning	Dynamic scheduling, reduced delays	Dependence on historical data	Singapore, Barcelona, London, Helsinki
Mobility	Smart Routing and MaaS	Multimodal Data Analysis	10-18% emission reductions	Real-time data integration	Helsinki (Whim), London (Citymapper), Stockholm
Mobility	Autonomous Vehicles	Graph Neural Networks	Energy-efficient operations, reduced collisions	Increased vehicle miles traveled	Helsinki, Dubai, Tokyo
Waste Management	Waste Sorting and Recycling	Computer Vision, Robotic Arms	High accuracy sorting, reduced contamination	High initial costs, variable conditions	Airports, hospitals, commercial centers
Waste Management	Predictive Waste Generation	Neural Networks, Support Vector Machines	Optimized collection routes, emission reductions	Inconsistent data collection	Spain (bin fill-level prediction)
Waste Management	Circular Economy Models	Analytics for Material Analysis	Enhanced reuse and recycling	Stakeholder coordination	Textile recycling in fashion industry
Environmental Monitoring	Water Leak Detection	CNN, SVM, Acoustic Sensors	Over 90% accuracy, reduced water loss	Noisy urban environments	Urban and agricultural networks
Environmental Monitoring	Air Pollution Prediction	Predictive Modeling, Satellite Imagery	Hotspot identification, targeted interventions	Data source integration	India (heat vulnerability modeling), Singapore
Urban Planning	Digital Twins and Simulation	Generative AI, 3D Modeling	Scenario testing, optimized planning	Data ownership and privacy	Houston, Singapore, Amsterdam
Urban Planning	Green Infrastructure Planning	Spatial Analytics, Hydrological Data	Urban cooling, stormwater management	Balancing environmental and equity goals	Sponge cities like Singapore

The paper is organized into sections covering AI in energy systems and infrastructure optimization, smart mobility, waste and water management, environmental sensing, and urban planning, followed by an exploration of ethical, technical, and governance issues, a forward-looking strategic roadmap, and a concluding analysis of research gaps and policy directions.

To provide a structured overview of the AI applications discussed in this review, Table 1 summarizes key implementations across major smart city domains, highlighting technologies, benefits, challenges, and examples drawn from the literature.

2. AI in Energy and Infrastructure Optimization

2.1. Smart Grids and Real-Time Demand Response Systems

AI is transforming smart grid operations by enabling real-time demand response mechanisms and dynamic energy balancing. Utility-scale systems now encourage smart-meter-equipped customers to reduce load during peak hours through incentives and automated responses, supported by intelligent scheduling algorithms. These AI-driven platforms allow grid operators to optimize supply, reducing reliance on costly peaking plants.

Utilities and technology firms are employing machine learning models to monitor transformer networks and anticipate failures, minimizing disruptions and curbing greenhouse gas emissions associated with unplanned outages. By leveraging anomaly detection and predictive maintenance, these systems enhance grid resilience under climate stress.

Smart grid initiatives, particularly in regions like China, have demonstrated significant load reductions in commercial and industrial sectors, ranging from 7% to 20% depending on operational conditions. These efforts underscore AI's capacity to optimize demand-side response across diverse sectors. As grids increasingly integrate distributed renewable generation and electrified loads, AI plays a critical role in maintaining stability. Real-time forecasting and optimization models, utilizing inputs such as weather, load, and asset status, enable dynamic demand response while preserving reliability. Combined with edge computing and IoT, these systems operate autonomously, continuously adapting to grid conditions in near real-time [8-10].

2.2. AI for Predictive Maintenance and Energy-Efficient Buildings

AI-driven predictive maintenance and building automation significantly enhance energy efficiency and operational resilience in urban infrastructure. Automated HVAC optimization systems, deployed across thousands of buildings globally, have demonstrated energy cost reductions of approximately 25% and substantial carbon emissions reductions by dynamically adjusting operations based on humidity, ventilation, and other environmental data. Machine learning and deep learning algorithms optimize indoor thermal comfort while minimizing energy consumption, effectively balancing occupant satisfaction with efficiency. However, the performance of these techniques often relies on high-quality sensor data, which can be a limitation in older buildings with sparse datasets.

AI-powered building management systems utilize circuit-level sensors and deep learning to identify inefficiencies, forecast consumption patterns, and preempt equipment failures in commercial facilities. These systems provide actionable insights for facility managers, enabling significant energy savings without requiring invasive retrofitting [11,12]. The integration of edge computing further enhances building management by enabling local data processing, which improves response times, strengthens data privacy, and reduces dependence on centralized data centers. Edge-based machine learning supports self-learning systems that continuously adapt to occupancy patterns, environmental conditions, and external factors such as weather forecasts, driving further improvements in building performance and sustainability.

2.3. Optimizing Public Infrastructure with Digital Twins and Sensors

Digital twins—virtual representations of physical infrastructure are increasingly utilized in smart cities to model, monitor, and optimize public assets. Cities such as Houston, Singapore, and Amsterdam are leveraging urban-scale digital twins to enhance climate resilience, manage transportation networks, and optimize waste systems, with projections indicating widespread adoption across hundreds of cities in the near future.

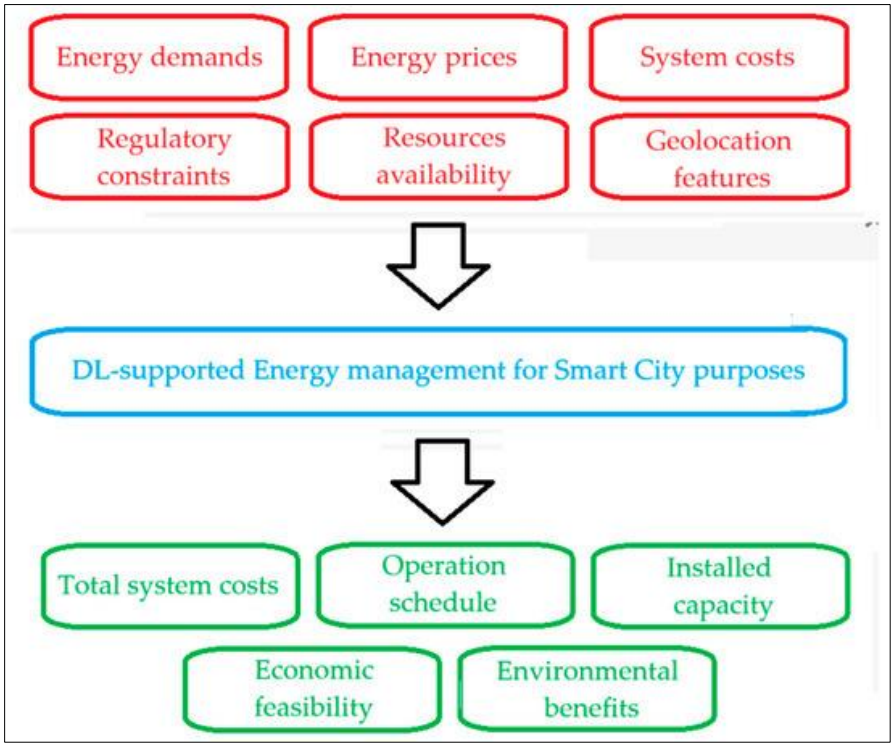
The architecture of the Internet of Digital Twins (IoDT) integrates physical and virtual entities through sensor networks, semantic communications, and dynamic synchronization, enabling predictive and optimized control of urban systems. These frameworks facilitate real-time decision-making across utilities, transportation networks, and public infrastructure, supporting efficient resource allocation and operational resilience.

Generative AI enhancements within digital twin platforms further enable autonomous scenario generation, 3D city modeling, and synthetic urban data augmentation. These capabilities support infrastructure planning and stress-testing by simulating interventions such as new transit routes, green infrastructure deployment, or building renovations under varying climate and urban growth scenarios. However, the deployment of digital twins introduces governance and privacy challenges. Issues such as data ownership, security vulnerabilities, and policy acceptance must be addressed to maintain public trust. Past challenges in cities like Portland and Toronto, where mobility data controversies arose, highlight the need for robust governance frameworks to ensure the ethical and secure implementation of digital twin technologies [6,13,14].

2.4. Role of AI in Urban Renewable Energy Integration

AI is instrumental in integrating distributed renewable energy resources into urban energy systems, enhancing efficiency and resilience. Machine learning models enable accurate forecasting of rooftop solar output, dynamically aligning local generation with demand and optimizing energy storage operations to minimize grid strain. These predictive capabilities ensure stable energy supply while maximizing the use of renewable sources. In smart cities, AI-managed microgrids play a critical role in balancing the variability of renewable energy outputs and facilitating demand response programs. By leveraging real-time analytics, these systems optimize battery dispatch, adjust building energy loads, and respond to supply fluctuations, fostering greener and more resilient urban energy ecosystems. AI algorithms also enable seamless coordination between distributed energy resources, such as solar photovoltaic (PV) systems, energy storage units, and electric vehicle (EV) charging infrastructure, reducing reliance on fossil fuel-based generation [15,16].

Beyond energy management, AI contributes to the design and implementation of green infrastructure. For instance, generative AI supports the development of innovative materials, such as thermally reflective coatings and paints, which reduce urban heat absorption. These advancements promote energy savings through passive cooling strategies, mitigating the urban heat island effect while enhancing sustainability at the material level. AI's integration across smart buildings, renewable energy systems, and green infrastructure strengthens urban energy resilience and accelerates decarbonization at the micro-urban scale. By coordinating distributed solar PV, storage, EV charging, and building loads, AI-driven optimization tools drive sustainable urban energy transitions, paving the way for low-carbon, future-ready cities [15-17]. To further elucidate the integration of deep learning in energy systems, Figure 1 illustrates the process through which DL supports energy optimization in smart cities, providing a visual workflow that complements the applications in smart grids, predictive maintenance, and renewable integration discussed herein.



Reproduced with permission from ref [16]

Figure 1 Process of possible DL support for energy optimization of smart cities

3. AI in Sustainable Urban Mobility

3.1. Intelligent Traffic Management Systems

Intelligent traffic management systems harness AI to enhance urban mobility by dynamically optimizing traffic signal timings, managing intersections, and predicting congestion patterns. These systems collect real-time data from sensors, cameras, and connected vehicles to forecast traffic density, adjust signal phases, and reroute flows to mitigate gridlock. Notable implementations demonstrate significant improvements in traffic efficiency and environmental outcomes. For instance, scalable urban traffic control systems have achieved reductions in travel times by approximately 25% and waiting times at intersections by up to 40% in real-world applications. In Sydney, Australia, an adaptive traffic control system utilizes inductive loops and real-time detection to tailor signal plans to current vehicle and pedestrian conditions, now deployed across over 55,000 intersections in 28 countries. Similarly, initiatives leveraging connected vehicle and navigation data optimize signals without requiring new hardware, yielding around a 30% reduction in idle stops and a 10% decrease in emissions in trial cities such as Seattle and Hamburg. These systems prioritize efficiency and sustainability by minimizing fuel consumption and reducing urban air pollution.

Emerging AI-IoT frameworks further advance traffic management by analyzing live CCTV feeds to assess vehicle counts and traffic density, enabling adaptive signal control. Simulation studies indicate these systems can improve flow efficiency by over 30%, offering cost-effective solutions by repurposing existing infrastructure. By integrating AI with IoT, cities can achieve scalable, data-driven traffic optimization that aligns with sustainable mobility goals.

Despite these advancements, the success of AI-driven traffic systems depends on robust institutional frameworks and legal enforcement. Challenges observed in deployments, such as in Nagpur, India, reveal that technological rollouts can be constrained by inadequate enforcement mechanisms or policy gaps. To maximize impact, cities must integrate AI tools with comprehensive policy strategies, ensuring technical capabilities are supported by governance structures that facilitate effective adoption and sustained performance [18-20]. Building on the discussion of intelligent traffic management, Figure 2 presents a proposed architecture for AI-driven adaptive traffic signal control, demonstrating how such systems can enhance urban mobility by reducing congestion and emissions in real-world scenarios.

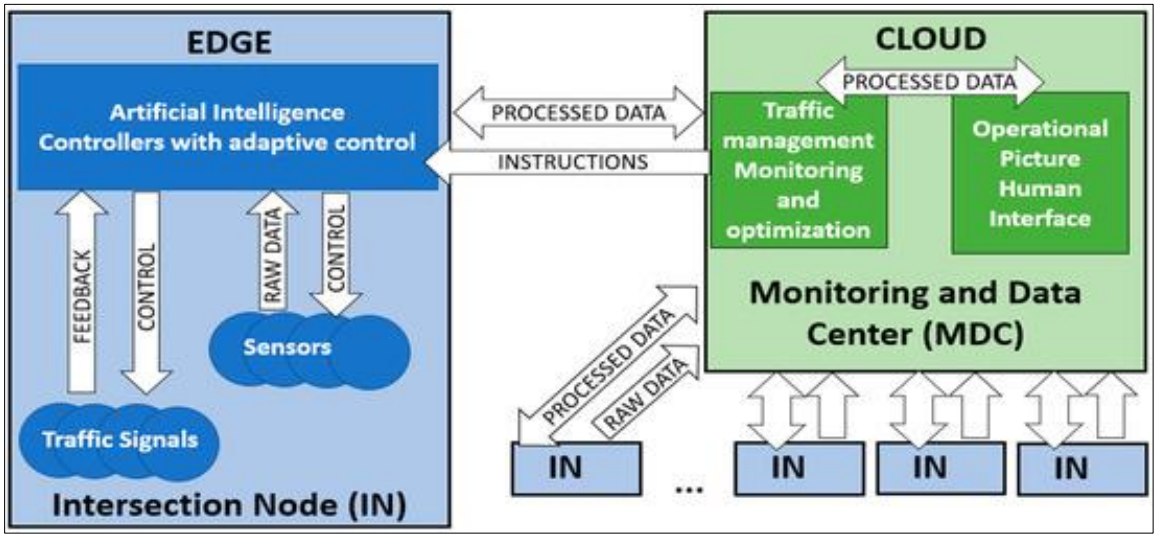


Figure 2 Proposed system architecture for AI-driven adaptive traffic signal control in Bucharest. Reproduced with permission from ref [19]

3.2. AI-Enabled Public Transportation Optimization

AI-enhanced public transportation systems significantly improve operational efficiency by predicting demand, optimizing routes and schedules, and delivering tailored services to passengers. Machine learning models, such as Random Forests, Gradient Boosting Machines, and Long Short-Term Memory (LSTM) networks, analyze diverse data sources including historical ridership patterns, real-time passenger flows, weather conditions, and local events to enable transit agencies to dynamically adjust service frequencies, prevent overcrowding, and enhance system reliability. For instance, advanced demand forecasting allows cities to optimize route choices, reduce travel times, and improve commuter experiences [21,22].

Reinforcement learning techniques further enhance public transport by continuously adapting routes and schedules based on live data, such as passenger demand, traffic congestion, and operational constraints. These adaptive systems improve service reliability, reduce fuel consumption, and minimize delays, contributing to more sustainable urban mobility. Additionally, AI-driven platforms integrate crowd-sourced passenger feedback to manage disruptions, redirect transit flows, and maintain service continuity in real time, ensuring a seamless commuter experience. AI also enables personalized passenger services through real-time alerts, adaptive routing recommendations, and virtual assistants. These tools provide commuters with tailored journey planning, real-time updates on delays, and alternative route suggestions, fostering greater engagement and encouraging public transit use. For example, AI-powered virtual assistants enhance user interaction by offering personalized travel guidance, improving accessibility and satisfaction in cities with complex transit networks [16,22].

Moreover, AI supports predictive maintenance by analyzing sensor data from vehicles and infrastructure to anticipate maintenance needs before failures occur. This proactive approach extends the lifespan of transit assets, reduces emissions associated with unscheduled downtime, and ensures consistent service availability, contributing to both operational efficiency and environmental sustainability. Cities such as Singapore, Barcelona, London, and Helsinki exemplify the adoption of AI in public transportation. Singapore's Land Transport Authority employs AI for demand forecasting and dynamic scheduling to optimize its extensive transit network. Barcelona leverages AI to enhance bus route efficiency, reducing wait times and improving service coverage. Helsinki pioneers AI-driven autonomous shuttles to complement its public transport system, while London uses AI to streamline ticketing processes and manage passenger flows, ensuring efficient and equitable access to transit services. By integrating these AI-driven solutions, cities can create responsive, sustainable, and user-centric public transportation systems that address the evolving demands of urban mobility [21-23].

3.3. Emissions Reduction through Smart Routing and Mobility as a Service (MaaS)

AI-powered mobility systems, such as Mobility as a Service (MaaS), integrate diverse transport modes including ridesharing, public transit, biking, and walking into cohesive platforms that optimize travel efficiency and minimize carbon emissions. These systems leverage AI to analyze multimodal data, generating optimal travel routes that balance cost, time, and environmental impact. Platforms like Whim in Helsinki and Citymapper in London exemplify this approach, offering integrated journey planning that reduces travel time and lowers carbon footprints by promoting sustainable transport options. In cities like Stockholm, AI combined with IoT enables dynamic routing for on-demand electric vehicles, adapting to real-time congestion and demand patterns. This reduces idle time and energy consumption, achieving emission reductions of approximately 10–18% in operational studies. Similarly, Tokyo employs AI to match passengers for shared autonomous electric shuttles, optimizing routes to enhance travel efficiency and reduce energy use compared to conventional transport services.

Smart routing systems, such as those incorporating real-time vehicle-to-infrastructure (V2I) communication, further contribute to emissions reduction by minimizing unnecessary stops and idling at intersections, particularly in areas with high pollution levels. For example, AI-driven traffic management systems optimize signal timings to improve traffic flow and reduce fuel consumption. Additionally, AI-enabled bike-sharing systems in cities like Copenhagen utilize historical and real-time data to strategically reposition bikes, encouraging modal shifts from fossil fuel-based transport to sustainable alternatives. By integrating predictive analytics and real-time data, AI-driven MaaS and smart routing systems consistently reduce travel times, operational costs, and carbon emissions. These advancements underscore AI's critical role in fostering sustainable urban mobility frameworks, supporting cities in achieving environmental goals while enhancing accessibility and efficiency for residents [24,25].

3.4. Autonomous Vehicles and Their Environmental Implications

Autonomous vehicles (AVs), encompassing shuttles, buses, and robo-taxis, hold transformative potential for urban mobility by optimizing routing, reducing collisions, and facilitating electrification. These vehicles leverage AI to enhance driving patterns, minimize unnecessary acceleration and deceleration, and coordinate fleets for energy-efficient operations, thereby reducing fuel consumption and emissions compared to traditional vehicles.

Pilot deployments in cities such as Helsinki and Dubai demonstrate the practical benefits of autonomous electric shuttles in low-density or last-mile transit corridors. These systems utilize AI to dynamically determine routes based on real-time passenger demand, improving accessibility while minimizing the environmental impact of underutilized conventional transit services. In Tokyo, AI-enabled autonomous shared-ride systems have reduced travel times and energy consumption without compromising safety or service coverage, offering a model for scalable, sustainable urban mobility. Advanced AI architectures, such as Graph Neural Networks (GNNs), further enhance AV capabilities by modeling complex spatio-temporal dependencies in transportation networks. These systems enable precise routing,

real-time traffic forecasting, and adaptive fleet management, supporting the scalability and resilience of AV deployments in dynamic urban environments.

Despite these advancements, AVs pose environmental risks if not strategically managed. Unregulated deployment may increase vehicle miles traveled by inducing travel demand, potentially exacerbating congestion and emissions. To maximize sustainability benefits, robust regulatory frameworks are essential. Policies should prioritize shared, electric AV fleets integrated with public transit systems to ensure efficient land use and reduced environmental footprints. By aligning AI-driven AV systems with urban sustainability goals, cities can harness their potential to create equitable, efficient, and environmentally responsible mobility networks [26-29].

4. AI in Waste Management and Circular Economy

4.1. AI for Waste Sorting and Recycling Systems

AI-enabled waste sorting technologies are revolutionizing recycling infrastructure, particularly in urban materials recovery facilities (MRFs). These systems leverage machine vision, robotic arms, and advanced algorithms to sort waste with high accuracy, significantly outperforming traditional manual sorting processes. By automating the classification of recyclables, such as plastics, metals, paper, and organic waste, AI enhances throughput, reduces contamination, and minimizes human exposure to hazardous workflows in recycling operations. Sophisticated AI models, utilizing deep convolutional neural networks, achieve near-real-time classification of waste materials with high precision. These systems integrate camera-based detection, servo-actuated sorting mechanisms, and IoT-enabled sensors to monitor bin fill levels and trigger collection alerts, seamlessly connecting sorting processes with operational logistics. Such integration optimizes waste collection routes and ensures timely processing, contributing to overall system efficiency.

From a design perspective, AI sorting systems address critical challenges like contamination, a major barrier to effective recycling. Smart waste bins equipped with onboard machine learning can identify and sort waste at the point of disposal while generating continuous audit data to improve system performance. These systems, deployed in public venues such as airports, hospitals, and commercial centers, achieve high sorting precision and engage users through visual feedback and interactive interfaces, fostering better recycling habits.

Despite their transformative potential, scaling AI-driven waste sorting systems faces technological and economic challenges. Achieving consistent precision across diverse waste streams and variable environmental conditions, such as fluctuating lighting, remains a technical hurdle. Additionally, high initial investment costs can limit adoption, particularly in resource-constrained urban settings. Ethical considerations, including privacy concerns related to camera-equipped bins or RFID-tagged waste tracking, necessitate robust governance frameworks to ensure transparency, data security, and public trust. Addressing these challenges is critical to advancing AI's role in supporting zero-waste strategies and circular economy principles in urban environments [30-32].

4.2. Predictive Analytics in Waste Generation and Collection

In smart waste ecosystems, predictive analytics significantly enhances planning by forecasting waste generation patterns and optimizing collection logistics. AI, integrated with IoT data, can substantially improve municipal waste management efficiency by reducing collection truck travel distances, operational time, and associated costs, while also lowering carbon emissions. Advanced techniques, including artificial neural networks, support vector machines, decision trees, and adaptive neuro-fuzzy inference systems, are employed to model municipal solid waste generation such as plastics, household packaging, and organic waste using historical socioeconomic, demographic, and waste-management data. These models support short-, medium-, and long-term forecasting, enabling both tactical operations, such as daily collection scheduling, and strategic infrastructure planning, including the placement of waste processing facilities.

A practical example from Spain demonstrates the efficacy of AI-supported systems, where software integrating bin fill-level prediction and route optimization minimizes unnecessary collection trips and emissions by dynamically adjusting routes based on real-time bin status. IoT-enabled sensors, combined with edge processing and machine learning, provide live data on waste levels, allowing for responsive and adaptive collection strategies that enhance service quality for citizens while reducing operational inefficiencies.

Despite these advancements, key limitations persist. Effective predictive modeling requires robust historical data and reliable, clean sensor feeds. In municipalities with inconsistent data collection or inadequate sensor infrastructure, model accuracy can suffer. Additionally, unpredictable shifts in social behavior, such as changes in consumption

patterns or waste disposal habits, can further challenge forecasting precision. Integration with broader urban planning systems remains critical to ensure that waste management aligns with city-wide sustainability goals, highlighting the need for cohesive data ecosystems and standardized data collection protocols [20,33,34].

4.3. Circular Economy Models Supported by AI Decision Systems

AI is increasingly instrumental in advancing circular economy principles by optimizing resource reuse, recycling, and production cycles within urban systems. By leveraging advanced analytics and machine learning, AI facilitates the integration of reverse logistics, waste management, supply chain optimization, recycling processes, and manufacturing redesign to close material loops, thereby reducing waste and enhancing resource efficiency.

AI-driven systems enhance material composition analysis through technologies such as hyperspectral imaging, QR codes, and RFID tagging. These tools guide product design for recyclability, assess packaging materials for efficiency, and evaluate reuse potential. For instance, AI-powered hyperspectral imaging systems enable precise sorting of complex waste streams, such as textiles, by identifying material compositions at a granular level, which supports recycling initiatives and promotes sustainable production practices in industries like fashion [35].

Additionally, AI-integrated platforms enhance waste traceability and transparency by combining real-time data analytics with geospatial tracking and blockchain-inspired verification systems. These platforms document waste collection processes, ensuring accurate tracking of material flows and enabling audit-ready circular interventions. Such technologies align waste streams with industrial reuse and recycling markets, fostering closed-loop systems that minimize environmental impact.

Despite these advancements, scaling AI-enabled circular economy frameworks faces significant challenges. Effective implementation requires coordinated collaboration among producers, consumers, and waste recovery enterprises to standardize data formats, establish consistent material labeling protocols, and develop robust markets for secondary materials. Without systemic integration, AI-based circular strategies risk remaining fragmented, limiting their transformative potential. Addressing these barriers through policy alignment, stakeholder engagement, and technological standardization is essential to fully realize AI's role in supporting sustainable, circular urban economies [35,36].

4.4. Industrial Symbiosis Planning with AI Tools

Industrial symbiosis, the coordinated sharing of materials, energy, and waste among proximate industries, is a proven strategy for enhancing resource efficiency in urban-industrial systems. Historically, symbiosis models, such as those implemented in eco-industrial parks like Kalundborg, relied on manual coordination to facilitate resource exchanges. However, AI introduces transformative potential by enabling scalable optimization of synergy networks through predictive analytics, real-time data integration, and advanced simulation tools.

AI-based decision support systems can analyze regional industrial flows, identify compatible by-product streams, and model potential exchanges for material reuse or energy recovery among firms. Unlike traditional approaches, these tools leverage dynamic matching algorithms and real-time production data to optimize resource flows, enhancing system resilience and minimizing cumulative waste. For instance, AI can map industrial outputs, such as excess heat or recyclable by-products, to the input needs of nearby facilities, creating efficient, closed-loop systems that reduce reliance on virgin resources. Emerging applications are evident in industrial zones where urban waste streams, such as construction debris or organic waste from food processing, are integrated into local manufacturing or composting ecosystems. AI-driven simulations enable scenario testing to identify optimal partner matching, logistics sequencing, and infrastructure configurations, ensuring cost-effective and environmentally sound outcomes. These tools also support the design of eco-industrial parks by quantifying reductions in environmental impact and creating value chains from waste streams, aligning with circular economy principles.

Despite its promise, the integration of AI into industrial symbiosis remains in its early stages. Current efforts are largely conceptual, with limited real-world implementation. Successful adoption requires robust public-private partnerships to fund pilot projects and establish platforms for secure, interoperable data exchange. Without shared governance frameworks and trust in data-sharing protocols, AI-driven industrial symbiosis tools may struggle to achieve widespread impact. Addressing these challenges is critical to unlocking the full potential of AI in fostering sustainable, resource-efficient industrial ecosystems [37-39].

5. AI in Water and Air Quality Management

5.1. Real-time Water Usage Monitoring and Leak Detection

Real-time water usage monitoring and leak detection are critical for sustainable urban water systems, addressing the global challenge of water loss, which can account for up to 30% of urban water supply in some cities. AI-enhanced systems integrate IoT sensors to monitor parameters such as pressure, flow rate, and temperature, enabling rapid identification of anomalies indicative of leaks. These systems employ machine learning algorithms to detect irregularities and trigger proactive response mechanisms, supporting both urban and agricultural water networks.

Advancements in AI-driven acoustic leak detection have significantly improved system reliability. Deep neural networks (DNN), convolutional neural networks (CNN), and support vector machines (SVM) consistently achieve over 90% accuracy in real-world settings, requiring minimal user training. These models analyze acoustic signals from pipe networks to pinpoint leaks, even in noisy urban environments. Additionally, machine learning approaches, such as random forests and neural networks, have been applied to synthetic sensor data, achieving leak detection rates of approximately 75%, demonstrating versatility across diverse water distribution networks [40].

Innovations in thermal imaging further enhance leak localization capabilities. By combining infrared thermography with hybrid CNN-LSTM architectures, AI systems can detect subsurface water losses with high precision. These models identify temperature anomalies associated with leaks, offering robust performance even in complex urban pipe networks with varying materials and configurations. This approach improves detection accuracy and supports predictive maintenance by forecasting potential failure points.

Beyond detection, AI optimizes sensor placement and predictive maintenance strategies. Graph-based feature selection methods strategically position sensors to maximize leak observability, reducing the number of devices needed compared to traditional uniform placement approaches. Similarly, genetic algorithms, such as GA-Sense, streamline sensor network design, enhancing detection efficiency while minimizing resource requirements. These advancements collectively reduce water loss, lower operational costs, and strengthen the resilience of urban water systems, ensuring sustainable management of this critical resource [17,41,42].

5.2. Air Pollution Detection, Prediction, and Hotspot Identification

AI-supported air quality monitoring has advanced through the integration of dense sensor networks, predictive modeling, and edge computing. Deployments utilizing both aerial and ground-based IoT sensors, coupled with machine learning algorithms, enable the collection of fine-grained pollutant data and short-term forecasting. These systems combine aerial and surface observations to provide accurate, power-efficient monitoring, delivering high-resolution insights into air quality dynamics across urban landscapes. In smart cities, AI models integrate diverse data sources, including satellite imagery, traffic patterns, meteorological conditions, and land-use metrics, to map pollution hotspots and predict exposure risks. For example, initiatives in India have employed satellite imagery alongside building and land-use data to model urban heat vulnerability at the building level, an approach that complements air quality modeling to identify at-risk neighborhoods. These predictive models enable targeted interventions, such as prioritizing green infrastructure or public health measures in densely populated or heat-exposed communities.

AI-driven digital twin systems, implemented in cities like Singapore, Houston, and Amsterdam, simulate urban environments, incorporating pollutants, traffic flows, and weather patterns. These models forecast areas where air quality may degrade, allowing planners to proactively deploy green buffers, reroute traffic, or issue public advisories. By simulating multiple scenarios, digital twins support preemptive strategies to mitigate air quality and heat-related stresses, enhancing urban resilience. The adoption of edge computing further enhances air quality management by enabling local processing of environmental sensor data. Edge-based systems, equipped with particulate matter and gas sensors, detect pollution spikes in real time, issuing rapid alerts and facilitating localized feedback loops. This approach reduces latency, conserves bandwidth, and enables more responsive air quality management, ensuring timely interventions to protect public health and improve urban livability [43-45].

5.3. AI-Supported Green Infrastructure Planning (e.g., Green Roofs, Parks)

AI is increasingly integral to the design and management of green infrastructure, such as green roofs, urban parks, and permeable pavements, in urban environments. By leveraging digital twins, AI enables cities to simulate and evaluate interventions like tree planting and green roof placement to mitigate urban heat islands and enhance sustainability. These systems analyze land use, building density, vegetation cover, and microclimate data to guide precise infrastructure upgrades, optimizing urban cooling, air quality, and aesthetic value [46].

AI enhances nature-based solutions, such as those seen in "sponge city" concepts, which prioritize permeable designs, wetlands, and other features for effective stormwater management and heat mitigation. By integrating AI with spatial, hydrological, and demographic data, cities can optimize the placement and design of green infrastructure to maximize climate resilience and environmental benefits. For instance, AI-driven models identify ideal locations for green roofs and urban parks, ensuring efficient stormwater absorption, reduced runoff, and improved urban biodiversity.

Digital twin platforms, such as those used in Singapore, combine AI with 3D GIS and simulation tools to test green infrastructure scenarios. These platforms enable "what-if" analyses to assess the impacts of proposed interventions on microclimate, ecosystem resilience, and energy efficiency. By simulating various configurations, cities can prioritize solutions that balance environmental performance with equitable access to green spaces, fostering inclusive urban development. AI also supports citywide planning frameworks by aligning green infrastructure with broader resilience and sustainability goals. For example, AI-driven models inform the development of urban parks and green corridors, integrating them into smart, green, and resilient planning strategies. This approach ensures that green infrastructure not only mitigates climate impacts but also enhances urban livability, promotes biodiversity, and supports equitable access to environmental benefits, contributing to holistic landscape-level sustainability [47-49].

5.4. Integration with IoT and Edge Computing in Environmental Sensing

The integration of AI with IoT and edge computing forms the backbone of scalable environmental sensing in smart cities, enabling real-time data collection and analysis for sustainable urban management. For instance, projects like Melbourne's AIoT CitySense demonstrate the potential of sensor-equipped municipal vehicles to collect roadside environmental data, including air quality, noise levels, and infrastructure leakage indicators. AI models process this data in real time, supporting predictive maintenance decisions, issuing system alerts, and enabling proactive urban governance. Edge computing enhances system responsiveness by enabling localized data processing near sensors, reducing latency and network load compared to centralized cloud-based systems. This architecture is critical for resource-constrained or privacy-sensitive urban deployments, where immediate environmental interventions such as rapid air quality alerts or water system alarms are essential. By processing data at the edge, cities can achieve faster response times and maintain operational efficiency even in bandwidth-limited environments.

The synergy of AI and IoT ecosystems supports predictive urban management by combining dynamic sensor networks with machine learning analytics. These systems enable cities to monitor pollution, ecosystem health, and infrastructure conditions proactively, shifting from reactive to anticipatory governance. For example, AI-enhanced remote sensing integrated with IoT networks can predict environmental trends, such as air quality degradation or water system inefficiencies, allowing city managers to implement timely interventions. This technology stack is further strengthened by advanced connectivity solutions, including 5G, low-power wide area networks (LPWAN), and fog/edge computing frameworks. These technologies facilitate real-time, scalable, and localized data capture, ensuring robust environmental monitoring. Platforms like the Aveiro Tech City Living Lab in Portugal exemplify this integration, combining mmWave, LoRaWAN, 5G, and edge devices to support environmental, mobility, and safety sensing. AI-infused analysis within these systems processes complex datasets to deliver actionable insights, enhancing urban resilience and sustainability. By merging environmental sensing with AI-driven decision support, these integrated systems create a foundation for intelligent, sustainable urban ecosystems capable of addressing current and future environmental challenges [50-52]. For a consolidated view of AI's role in environmental management, Table 2 outlines applications in water and air quality, including methods, metrics, integrations, benefits, and examples.

Table 2 AI Applications in Water and Air Quality Management

Application	AI Method	Key Metrics	Integration Technologies	Benefits	Examples/Regions
Water Leak Detection	DNN, CNN, SVM	>90% accuracy	Acoustic Sensors, IoT	Reduced 30% water loss	Urban pipe networks
Water Usage Monitoring	Anomaly Detection	Rapid identification	Pressure/Flow Sensors	Proactive responses	Agricultural and urban systems
Thermal Leak Localization	CNN-LSTM	High precision in subsurface	Infrared Thermography	Predictive maintenance	Complex pipe configurations
Sensor Placement Optimization	Graph-Based, Genetic Algorithms	Maximized observability	GA-Sense Framework	Fewer sensors needed	Water distribution networks
Air Pollution Detection	Predictive Modeling	Fine-grained forecasting	Satellite Imagery, IoT Sensors	Hotspot mapping	India, Addis Ababa
Pollution Hotspot ID	Machine Learning Analytics	Exposure risk prediction	Traffic/Meteorological Data	Targeted interventions	Building-level modeling
Digital Twin Simulation	Scenario Forecasting	Degradation predictions	3D GIS, Weather Patterns	Preemptive strategies	Singapore, Houston, Amsterdam
Edge Computing Sensing	Real-time Alerts	Spike detection	Particulate/Gas Sensors	Reduced latency	Urban environments
Green Infrastructure Planning	Spatial Analytics	Optimized placement	Hydrological/Demographic Data	Urban cooling, biodiversity	Sponge cities
Stormwater Management	What-If Analyses	Impact assessments	Simulation Tools	Resilience enhancement	Singapore's platforms

6. Social, Ethical, and Environmental Justice Dimensions

6.1. Privacy Concerns in Urban AI Deployments

The widespread deployment of IoT sensors, surveillance cameras, and AI-driven analytics in smart cities has intensified concerns about citizen privacy. The reliance on continuous data collection in urban environments risks eroding individual anonymity, a phenomenon often described as digital panopticism. This dynamic creates a tension between the benefits of urban intelligence such as optimized public services and the preservation of personal autonomy. Surveillance infrastructures, initially designed for operational efficiency, can be repurposed for control and enforcement, which undermines public trust in smart city systems. Privacy in this context extends beyond mere data protection; it is a societal norm integral to individual dignity and autonomy. Public apprehension often centers on the lack of clarity regarding the purpose of data collection, the mechanisms for obtaining consent, and whether data serves community goals or private interests. Without transparent data-use protocols embedded in smart city design, data-driven innovations risk alienating citizens and eroding trust in governance [21,54].

Emerging technical solutions offer pathways to mitigate these privacy risks. Techniques such as differential privacy, federated learning, homomorphic encryption, and blockchain can safeguard data confidentiality while enabling robust analytics for urban applications. Additionally, AI-based surveillance systems can incorporate real-time anonymization to minimize exposure of personal data, aligning with privacy-by-design principles. These privacy-enhancing technologies (PETs) provide a framework for balancing urban efficiency with the protection of individual rights. However, implementing PETs presents challenges, including limited scalability, interoperability issues, and low public awareness. A significant barrier is the "transparency paradox," where increased data-related information does not necessarily lead to greater public understanding or meaningful consent. To address this, smart city initiatives must prioritize not only the deployment of PETs but also robust public communication and digital literacy programs. Engaging communities through clear, accessible information about data practices and their implications is essential for fostering trust and ensuring that smart city technologies serve the public interest while upholding ethical standards [53,54].

6.2. Algorithmic Fairness in Resource Allocation

Smart city systems increasingly rely on automated decision-making to manage critical urban functions, such as allocating parking permits, public housing, or traffic enforcement. However, these algorithmic systems are prone to embedded biases, which can disproportionately impact marginalized communities. For instance, opaque municipal algorithms used in housing, justice, and welfare allocation may lack transparency and accountability, leading to discriminatory outcomes that exacerbate existing inequities.

To address these challenges, emerging frameworks focus on mitigating bias in urban data-driven systems while accounting for their spatio-temporal complexities. One such approach involves logic-based fairness rules designed to reduce bias in predictive allocation tasks. Evaluations in cities like Chattanooga demonstrate that these methods can maintain fairness dynamically without compromising system performance, ensuring equitable resource distribution across diverse urban populations. Visual analytic tools further support fair urban planning by enabling planners to visualize disparities, explore counterfactual scenarios, and recommend equitable resource allocations through constraint-based simulations. These tools integrate fairness into planning workflows, prioritizing equity as a core component rather than an afterthought. For example, such frameworks allow urban planners to assess the impact of resource allocation decisions on different demographic groups, ensuring that interventions address systemic inequalities [55,56].

Despite these advances, achieving consistent fairness in smart city systems remains a challenge. Without deliberate design, smart city initiatives risk disproportionately benefiting affluent populations, leaving marginalized groups underserved. Governance structures often lack sufficient public participation or oversight, further undermining equitable outcomes. To overcome these barriers, fairness frameworks must be coupled with participatory governance models that prioritize inclusive stakeholder engagement. This includes involving community representatives in decision-making processes, ensuring transparency in algorithmic operations, and establishing robust accountability mechanisms. By aligning technical solutions with inclusive governance, smart cities can better ensure equitable resource allocation and foster trust across diverse urban populations [55,57].

6.3. Inclusion of Vulnerable Populations in Smart Planning

Smart city initiatives often fail to account for socio-economic diversity and access disparities, disproportionately affecting vulnerable communities in low-income neighborhoods, informal settlements, and cities in the Global South.

These groups frequently lack the data infrastructure, digital literacy, or political representation necessary to inform or benefit from AI-driven urban systems. Without deliberate efforts, smart city technologies risk exacerbating existing inequities rather than addressing the root causes of urban injustice [57].

Human-centered design is critical to fostering inclusive smart planning. Research highlights concern among citizens about algorithmic invisibility, where automated systems make decisions without transparency or consent, even when intended to serve communal benefits. Such concerns underscore the need for participatory approaches that prioritize user agency and trust. Furthermore, achieving a balance between urban resilience and civil liberties requires intentional system design that avoids excessive surveillance or profiling of vulnerable populations under the pretext of efficiency. Instead, smart city frameworks must promote public engagement to ensure legitimacy and inclusivity, incorporating diverse voices in decision-making processes. To achieve equitable outcomes, smart city planning must include targeted infrastructure investments and capacity-building programs in underserved areas. These efforts should focus on improving digital access, enhancing data literacy, and empowering local communities to actively participate in and benefit from smart systems. For example, deploying community-based data collection tools and providing training on digital platforms can bridge gaps in access and representation. Without such measures, smart city initiatives risk entrenching systemic exclusion, perpetuating disparities under the guise of technological progress. By prioritizing inclusivity, cities can ensure that smart systems serve all residents, fostering equitable, resilient, and sustainable urban environments [58,59].

6.4. Governance Frameworks for Accountable AI in Urban Systems

Effective governance is essential to ensure AI deployments in urban systems uphold ethical standards while delivering public value. As cities increasingly integrate AI into critical functions such as infrastructure management, mobility, and resource allocation, the need for robust regulatory oversight and transparent decision-making processes becomes paramount. Governance frameworks must prioritize accountability, public trust, and inclusivity to mitigate risks such as opaque decision-making, bias amplification, and erosion of privacy. Multi-stakeholder governance models are recommended to foster collaboration among urban planners, data scientists, civil society organizations, and residents. These models promote participatory decision-making, ensuring diverse perspectives shape AI deployment strategies. By involving communities in the governance process, cities can enhance public trust, address local needs, and embed accountability into AI systems. For instance, inclusive engagement helps identify potential biases in algorithms and ensures solutions align with societal values, such as equity and sustainability [33,52,60].

Technical tools, including privacy-enhancing technologies (PETs), logic-based fairness systems, and visual analytics, play a critical role in supporting accountable AI. PETs, such as differential privacy and federated learning, safeguard sensitive data while enabling robust analytics. Logic-based fairness systems help detect and mitigate biases in AI models, ensuring equitable outcomes. Visual analytics provide interpretable insights into AI decision-making processes, enhancing transparency for stakeholders. However, these tools must be integrated within broader regulatory frameworks, such as data protection regulations or local city charters, to ensure compliance and enforce ethical standards.

Transparent mechanisms, such as public algorithmic registries, are vital for demystifying AI operations. These registries document the purpose, data sources, and decision-making logic of AI systems, enabling public scrutiny and fostering trust. Cities can draw inspiration from existing efforts to implement such registries, tailoring them to local contexts. Additionally, ethical design principles must be embedded in AI systems from the planning phase through deployment, ensuring fairness, accountability, and alignment with public interest. Accountable AI in urban environments demands governance frameworks that integrate legal standards, inclusive public engagement, transparent mechanisms, and ethically designed systems. By combining regulatory oversight with participatory models and advanced technical tools, cities can harness AI's potential to create equitable, sustainable, and resilient urban systems while maintaining public trust and accountability [43,61]. Table 3 synthesizes the ethical, social, and governance challenges associated with urban AI deployments, along with impacts, mitigation strategies, stakeholders, and references for targeted analysis.

Table 3 Ethical, Social and Governance Challenges in Urban AI

Challenge Category	Specific Issue	Potential Impacts	Mitigation Strategies	Affected Stakeholders	References
Privacy Concerns	Data Collection in Surveillance	Erosion of anonymity	Differential Privacy, Federated Learning	Citizens, Vulnerable Groups	[21,53-54]
Privacy Concerns	Digital Panopticism	Loss of autonomy	Anonymization, PETs	General Public	[53-54]
Algorithmic Fairness	Bias in Resource Allocation	Disproportionate impacts on marginalized	Logic-Based Fairness Rules	Low-Income Communities	[55-57]
Algorithmic Fairness	Opaque Algorithms	Discriminatory outcomes	Visual Analytic Tools	Housing/Justice Recipients	[55-56]
Inclusion Issues	Digital Access Disparities	Exclusion of vulnerable populations	Capacity-Building Programs	Global South, Elderly	[57-59,65-66]
Inclusion Issues	Algorithmic Invisibility	Lack of consent	Participatory Governance	Informal Settlements	[58-59]
Governance Frameworks	Lack of Accountability	Bias Amplification	Public Algorithmic Registries	Urban Planners, Residents	[33,52,60-61]
Governance Frameworks	Opaque Decision-Making	Eroded Public Trust	Multi-Stakeholder Models	Civil Society Organizations	[43,61]
Environmental Justice	Surveillance Profiling	Inequitable Benefits	Ethical Design Principles	Marginalized Groups	[57]
Environmental Justice	Job Displacement Risks	Socio-Economic Inequities	Workforce Training	Municipal Workers	[39,62-63]

7. Barriers to Implementation and Scalability

7.1. Data Fragmentation and Siloed Infrastructure

Data fragmentation and siloed infrastructure pose significant challenges to the effective deployment of AI in smart cities. Urban services, including transportation, energy, waste management, and environmental monitoring, are often managed independently by various departments and vendors, resulting in disparate systems and incompatible datasets. This lack of interoperability hinders the generation of cohesive insights across urban domains, limiting the potential for scalable AI solutions that rely on integrated data to optimize city-wide operations. The diversity in data formats, schemas, quality, and API protocols further complicates integration efforts. Inconsistent and unstructured data sources create significant obstacles, often causing AI initiatives to stall due to integration challenges rather than deficiencies in algorithmic models. For instance, variations in sensor data from different vendors or misaligned data collection standards can prevent seamless communication between systems, undermining the effectiveness of AI-driven applications such as real-time traffic management or energy optimization [62,63].

Addressing these challenges requires the adoption of standardized ontologies, communication protocols, and open data platforms to enable interoperability and facilitate city-wide scalability. Smarter integration frameworks, incorporating human oversight and robust data abstraction layers, are essential to manage the complexity of urban data ecosystems. However, few cities have successfully implemented such frameworks, as coordination between departments and vendors remains a persistent barrier. The absence of unified data architectures not only limits the technical performance of AI systems but also jeopardizes their long-term sustainability, as fragmented systems struggle to support scalable, cross-domain solutions. Overcoming these obstacles demands collaborative governance models and investments in shared digital infrastructure to align stakeholders and enable the seamless flow of data across urban systems [50,62,64].

7.2. Financial and Institutional Barriers to AI Uptake

The deployment of AI in smart cities faces significant financial and institutional challenges that hinder widespread adoption. Financial constraints are a primary barrier, as the implementation of advanced technologies such as sensor networks, edge computing infrastructure, and 5G connectivity demands substantial capital investment. These costs often exceed the budgetary capacity of municipal governments, particularly in developing regions with limited fiscal resources. As a result, many AI-driven smart city initiatives remain trapped in "pilot purgatory," where small-scale testbeds struggle to secure sustainable funding for city-wide expansion. To address this, innovative financing models, such as public-private partnerships, phased implementation strategies, and outcome-based procurement, are essential to bridge funding gaps and ensure scalability. However, the adoption of such models remains inconsistent, limiting their impact.

Institutional barriers further complicate the deployment of AI in smart cities. Departmental fragmentation within municipal governments often leads to siloed budgets and priorities, undermining the cross-departmental coordination required for integrated smart city projects. Effective AI implementation necessitates collaboration among diverse sectors, including transportation, energy, utilities, urban planning, and information technology. Yet, misaligned objectives and limited inter-departmental communication hinder cohesive financial planning and project execution. Establishing centralized governance frameworks or dedicated smart city task forces can help align departmental efforts and streamline resource allocation.

Additionally, institutional inertia and resistance to change pose significant hurdles. Bureaucratic bodies may hesitate to adopt AI-enabled systems due to concerns over accountability, potential job displacement, or insufficient technical expertise among staff. Unclear or outdated procurement processes further exacerbate these challenges, delaying project timelines and discouraging innovation. To overcome these barriers, institutional modernization is critical, including investments in workforce training to build technical capacity, clear policy frameworks to guide procurement, and strong political leadership to champion smart city initiatives. Such measures are vital to translate visionary AI-driven smart city strategies into systemic, scalable deployment, ensuring cities can fully leverage AI to address urban challenges effectively [43,39,62,63].

7.3. Capacity Building and Digital Literacy Gaps

The successful implementation of AI in smart cities hinges on the availability of skilled personnel proficient in data science, urban planning, ethics, and systems integration. However, global shortages in these competencies pose significant barriers to realizing AI's full potential. A critical challenge is the widespread digital skills gap, which limits the ability to deploy AI-driven solutions effectively, particularly in environmental and urban sustainability applications.

This gap encompasses deficiencies in AI literacy, data governance expertise, and the ethical competence required to ensure responsible technology deployment. In many regions, particularly in developing economies, educational systems are ill-equipped to address these needs. For instance, in numerous African countries, only a limited number of universities offer accredited AI programs, and these often lack practical training tailored to urban or environmental challenges. This educational shortfall is exacerbated by uneven access to digital infrastructure, with billions of people globally remaining offline, hindering both workforce development and public engagement with AI-enabled urban services.

Digital literacy disparities further complicate smart city adoption within urban populations. Studies from diverse regions, such as Indonesia and Nigeria, reveal significant variations in technology awareness and comfort levels, with older generations and marginalized communities frequently excluded from meaningful participation in smart city initiatives. To address these challenges, comprehensive capacity-building strategies are essential [65,66]. These should include sustained investments in AI-focused education, practical training programs aligned with urban sustainability goals, and expanded access to digital infrastructure. Additionally, culturally sensitive outreach and inclusive stakeholder engagement are critical to fostering equitable participation, ensuring that smart city technologies benefit diverse urban populations and contribute to inclusive, sustainable urban development.

7.4. Legacy Infrastructure Constraints and Interoperability Issues

Many cities rely on aging infrastructure transport networks, utilities, and water systems not originally designed to support smart sensors, data analytics, or real-time connectivity. Retrofitting these legacy systems to accommodate AI-driven technologies is often costly, technically complex, and impractical at scale, particularly when systems are rigid or lack comprehensive documentation. Consequently, cities face critical trade-offs between pursuing comprehensive modernization and implementing incremental upgrades, balancing cost, feasibility, and performance. Interoperability challenges further complicate the integration of legacy infrastructure with modern smart city frameworks. Many legacy systems operate on proprietary interfaces or outdated standards, which are incompatible with contemporary data formats and communication protocols. This lack of standardization creates silos, hindering seamless data exchange and integration across urban domains such as energy, transportation, and waste management. Even as cities adopt advanced sensor networks, these interoperability bottlenecks limit the ability to aggregate insights across systems, reducing the overall effectiveness of AI-driven solutions and impeding holistic urban optimization [60,66].

Cybersecurity and public trust present additional hurdles in integrating legacy systems with smart technologies. Older infrastructure often lacks robust security architectures, making it vulnerable to cyber threats as smart overlays expand. Ensuring secure, interoperable, and privacy-preserving systems is critical not only for operational functionality but also for fostering public confidence in AI-enabled urban services. Without addressing these vulnerabilities, cities risk data breaches and eroded trust, which could undermine the adoption of smart city initiatives. To overcome these challenges, strategic investments in standardized protocols, modular system designs, and robust cybersecurity frameworks are essential to bridge the gap between legacy infrastructure and future-ready urban ecosystems.

8. Future Outlook and Research Directions

8.1. Emerging Technologies (Federated Learning, Neurosymbolic AI)

Federated learning (FL) is emerging as a transformative approach for smart city infrastructures, enabling privacy-preserving machine learning across distributed devices. By training models locally on heterogeneous urban systems such as IoT sensors, smart meters, and mobility networks FL eliminates the need to centralize sensitive raw data, addressing privacy and data minimization concerns critical for urban applications. This decentralized approach enhances user convenience and system security while optimizing domains like energy management, mobility, and environmental monitoring. Additionally, green federated learning prioritizes energy-efficient algorithms, reducing the computational carbon footprint in resource-constrained edge environments, aligning with sustainability goals for smart cities.

Neurosymbolic AI, which integrates neural deep learning with symbolic reasoning, offers robust and interpretable models tailored for urban decision support and planning. By combining data-driven pattern recognition with rule-based reasoning, neurosymbolic architectures excel in tasks such as routing optimization, policy simulation, and anomaly detection in complex urban systems. In digital twin frameworks, neurosymbolic AI enhances the ability to model urban planning scenarios by blending predictive analytics with human-understandable logic, enabling more transparent and effective decision-making for sustainable urban development [67,68].

The synergy of FL and neurosymbolic AI holds significant potential for the future of smart cities. FL supports collaborative learning across distributed urban devices while safeguarding privacy, while neurosymbolic AI ensures models remain interpretable and trustworthy. Together, they enable resilient, adaptive intelligent systems capable of navigating the dynamic and multifaceted challenges of urban environments. Complementary technologies, such as Edge AI, 5G connectivity, and blockchain, further enhance these systems. Edge AI enables low-latency computation at the network's edge, 5G ensures high-speed, reliable data transfer, and blockchain provides secure, transparent data provenance. Integrating these technologies with policy and governance frameworks that prioritize sustainability, resilience, and equity will be critical to realizing the full potential of AI-driven smart city solutions. Future research should focus on developing scalable, interoperable platforms that combine these emerging technologies, ensuring inclusive and ethical deployment to address the evolving needs of urban populations.

8.2. Interdisciplinary Collaboration and Public-Private Partnerships

The effective integration of AI into smart cities requires robust, coordinated collaboration across diverse sectors to ensure that technological advancements align with societal needs. Smart city initiatives thrive when city governments, academic institutions, private technology firms, civil society organizations, and community stakeholders engage in multi-faceted partnerships. These cooperative models foster innovation by leveraging the unique strengths of each sector, including technical expertise, local knowledge, and governance capabilities, to create scalable, impactful urban solutions. Regional initiatives, such as the ASEAN Smart Cities Network, exemplify cross-jurisdictional collaboration, bringing together governments, private sector entities, and academic institutions to develop standardized frameworks, secure funding, and implement smart city projects that enhance urban resilience and sustainability. These partnerships facilitate knowledge exchange, streamline resource allocation, and ensure that solutions are contextually relevant and scalable across diverse urban environments [50,69].

A people-centered approach, as emphasized by global urban development frameworks, underscores the importance of aligning AI-driven innovations with the goals of inclusive, safe, resilient, and sustainable urban development, as outlined in Sustainable Development Goal 11. Public-private-people partnerships are critical to balancing the profit-driven motives of private entities with the public sector's commitment to equity, accessibility, and environmental sustainability. These partnerships prioritize transparency, accountability, and community engagement to ensure that AI applications in mobility, energy, waste management, and urban services enhance public welfare without exacerbating inequalities. Interdisciplinary collaboration is equally vital, uniting AI specialists, urban planners, environmental scientists, sociologists, legal scholars, and ethics experts to address the multifaceted challenges of smart city development. Such teams are essential for designing AI systems that prioritize human well-being, transparency, trust, and privacy. By integrating ethical considerations and social inclusion into the development process, interdisciplinary approaches enhance the legitimacy, adoption, and long-term impact of smart city initiatives, ensuring that technological advancements serve as a force for equitable and sustainable urban progress.

8.3. Citizen-Centered AI Design for Sustainable Cities

Citizen-centered AI design places urban residents at the heart of smart city strategies, ensuring technologies address authentic human needs while promoting equity and inclusivity. By prioritizing human-centric approaches, AI applications in sectors such as traffic management, healthcare, and environmental services enhance transparency, foster social acceptance, and improve service delivery. Structured participatory processes, including public consultations and co-creation initiatives, build trust and align AI systems with community priorities, strengthening public legitimacy. Transparent data policies, clear communication about AI-driven decisions, and robust feedback mechanisms are critical for effective governance. These elements ensure accountability and enable residents to engage meaningfully with urban systems. Multisectoral planning that incorporates citizen voices, as emphasized in global urban development frameworks, further reinforces accountability while aligning AI deployment with sustainable urban goals.

Addressing digital access and inclusion is paramount to prevent smart city models from marginalizing low-income or digitally underserved populations. Equity-focused design requires removing barriers to participation, such as limited access to technology or digital literacy gaps [65,67]. AI systems must facilitate participatory governance through two-way feedback loops, empower stakeholders with clear and accessible information, and involve communities in co-designing urban services. By embedding equity and inclusion into both governance and technical frameworks, AI can drive sustainable progress toward urban development goals, ensuring technological innovation benefits all residents equitably and contributes to resilient, inclusive cities.

8.4. Aligning Urban AI Development with SDGs and Climate Targets

Aligning AI development in smart cities with the Sustainable Development Goals (SDGs) and Paris climate targets is essential to ensure that technological advancements support both social equity and environmental sustainability. AI-enabled urban systems can deliver significant co-benefits, such as reduced greenhouse gas emissions, improved access to essential services like clean water and energy, and enhanced urban resilience. However, these systems also present challenges, including the energy-intensive nature of AI operations and potential risks of increased surveillance, necessitating robust governance frameworks to mitigate trade-offs and ensure equitable outcomes. Mapping AI applications to specific SDGs, such as SDG 11 (Sustainable Cities and Communities) and SDG 13 (Climate Action), fosters strategic coherence and strengthens policy integration across urban sectors [70]. For instance, AI-driven solutions like federated learning, edge AI, and IoT sensor networks, when integrated with renewable energy sources, enable low-carbon urban infrastructures. These technologies support dynamic demand management, resilient service delivery, and real-time carbon emissions monitoring, aligning with net-zero objectives and enhancing urban adaptability to climate challenges.

To balance digital innovation with sustainability imperatives, governance frameworks must prioritize auditability, transparency, and climate-aligned performance metrics in AI systems for urban management. Ethical AI policies should emphasize environmental justice and user well-being, ensuring that AI contributes to broader societal goals beyond mere efficiency gains. This includes designing systems that minimize energy consumption, promote inclusive access to services, and address disparities in urban digital infrastructure.

Furthermore, transnational and inter-city collaborations play a pivotal role in scaling AI ecosystems that align with SDGs and climate targets. Platforms such as the ASEAN Smart Cities Network and initiatives under UN-Habitat facilitate knowledge sharing, resource exchange, and harmonized policy development. These cross-regional partnerships enable cities to learn from best practices, adapt scalable solutions, and coordinate actions to address shared challenges in sustainable urban development. By fostering such collaborations, cities can accelerate the deployment of AI-driven systems that support global sustainability goals while addressing local urban priorities.

9. Conclusion

AI is a cornerstone of the smart city framework, equipping urban systems with advanced capabilities to tackle complex sustainability challenges. Its applications span optimizing transportation networks, reducing energy consumption in buildings, enabling precise environmental monitoring, and fostering active citizen participation. By enhancing efficiency, responsiveness, and predictive accuracy, AI fundamentally reshapes urban operations. Real-world implementations demonstrate that AI integration improves infrastructure performance and supports climate mitigation by enabling low-carbon transitions and advancing circular economy principles. For instance, AI-enabled smart energy grids have achieved significant reductions in peak energy demand, highlighting the transformative potential of cohesive governance, institutional support, and robust data-sharing mechanisms in accelerating sustainable urban transformations.

Despite its promise, realizing AI's full potential for sustainable urbanism faces several challenges. Issues such as algorithmic fairness, unequal access to AI resources, high energy demands for model training, and fragmented policy landscapes hinder effective implementation. The lack of interoperable data standards across urban systems further complicates scaling AI solutions. Overcoming these barriers requires robust interdisciplinary collaboration among computer scientists, urban planners, environmental engineers, and policymakers to develop AI systems that are technologically advanced and socially inclusive. Policy priorities should emphasize ethical AI deployment, transparent data governance, climate justice, and meaningful stakeholder engagement to ensure equitable distribution of benefits. Additionally, establishing regulatory frameworks, incentivizing green AI innovation, and embedding sustainability metrics into AI development processes are essential for aligning intelligent urban systems with the broader goals of sustainable development. By addressing these challenges, cities can harness AI to create resilient, equitable, and sustainable urban environments capable of meeting the demands of a rapidly changing world.

Compliance with ethical standards

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References

[1] Shahidehpour, M., Li, Z., and Ganji, M. (2018). Smart cities for a sustainable urbanization: Illuminating the need for establishing smart urban infrastructures. IEEE Electrification magazine, 6(2), 16-33.

[2] Makvandi, M., Li, W., Li, Y., Wu, H., Khodabakhshi, Z., Xu, X., and Yuan, P. F. (2024). Advancing Urban Resilience Amid Rapid Urbanization: An Integrated Interdisciplinary Approach for Tomorrow's Climate-Adaptive Smart Cities—A Case Study of Wuhan, China. Smart Cities, 7(4), 2110-2130.

[3] Daniela, K. N., Renata, P. N., and Mimoza, B. J. (2025). Exploring Pathways on How Artificial Intelligence is Shaping Safer, Smarter, Greener Cities. In TTS 2025 Conference 4th International Scientific Conference" TRANSPORT FOR TODAY'S SOCIETY". University "St. Kliment Ohridski"–Bitola, Faculty of Technical Sciences–Bitola.

[4] Yigitcanlar, T., Hossain, S. T., Shaamala, A., and Ye, X. (2025). Quantum AI urbanism: redefining the future of artificial intelligence in cities. Journal of Urban Technology, 1-14.

[5] Shulajkovska, M., Smerkol, M., Noveski, G., and Gams, M. (2024). Enhancing urban sustainability: developing an open-source AI framework for smart cities. Smart Cities, 7(5), 2670-2701.

[6] Satpathy, I., Nayak, A., and Jain, V. (2025). The green city: Sustainable and smart urban living through artificial intelligence. In Utilizing Technology to Manage Territories (pp. 273-304). IGI Global.

[7] Al‐Raeei, M. (2025). The smart future for sustainable development: Artificial intelligence solutions for sustainable urbanization. Sustainable development, 33(1), 508-517.

[8] Khan, M. A., Saleh, A. M., Waseem, M., and Sajjad, I. A. (2022). Artificial intelligence enabled demand response: Prospects and challenges in smart grid environment. Ieee Access, 11, 1477-1505.

[9] Stanelyte, D., Radziukyniene, N., and Radziukynas, V. (2022). Overview of demand-response services: A review. Energies, 15(5), 1659.

[10] Wei, T., Li, H., and Miao, J. (2025). Integration and Development Path of Smart Grid Technology: Technology-Driven, Policy Framework and Application Challenges. Processes, 13(8), 2428.

[11] Oyetunji, T. S., Erinjogunola, F. L., Ajirotutu, R. O., Adeyemi, A. B., Ohakawa, T. C., and Adio, S. A. (2024). Predictive AI models for maintenance forecasting and energy optimization in smart housing infrastructure. International Journal of Advanced Multidisciplinary Research and Studies, 4(6), 1372-1380.

[12] Bajwa, A., Jahan, F., and Ahmed, I. (2024). A Systematic Literature Review On AI-Enabled Smart Building Management Systems For Energy Efficiency And Sustainability. Noor alam and Ahmed, Ishtiaque, A Systematic Literature Review On Ai-Enabled Smart Building Management Systems for Energy Efficiency and Sustainability (December 15, 2024).

[13] Wu, D., Zheng, A., Yu, W., Cao, H., Ling, Q., Liu, J., and Zhou, D. (2025). Digital twin technology in transportation infrastructure: a comprehensive survey of current applications, challenges, and future directions. Applied Sciences, 15(4), 1911.

[14] Tommy, A. S., and Jaya, R. P. (2025). Integration of AI and Digital Twin Technology for Smart Infrastructure Management in Urban Cities. Civil Engineering Science and Technology, 1(1), 45-62.

[15] Singar, M. K., Suneetha, K., Saraswat, N., and Shukla, G. (2024). Artificial Intelligence's Role in Shaping Renewable Energy for Next-Generation Smart Cities. In E3S Web of Conferences (Vol. 540, p. 08014). EDP Sciences.

[16] Rojek, I., Mikołajewski, D., Galas, K., and Piszcz, A. (2025). Advanced Deep Learning Algorithms for Energy Optimization of Smart Cities. Energies, 18(2), 407.

[17] Singh, B., and Kaunert, C. (2024). Dynamic landscape of artificial general intelligence (agi) for advancing renewable energy in urban environments: Synergies with sdg 11—sustainable cities and communities lensing policy and governance. In Artificial General Intelligence (AGI) Security: Smart Applications and Sustainable Technologies (pp. 247-270). Singapore: Springer Nature Singapore.

[18] Dikshit, S., Atiq, A., Shahid, M., Dwivedi, V., and Thusu, A. (2023). The use of artificial intelligence to optimize the routing of vehicles and reduce traffic congestion in urban areas. EAI endorsed transactions on energy web, 10, 1-13.

[19] Andrei, N., and Scarlat, C. (2025). AI-driven urban mobility solutions: Shaping Bucharest as a smart city. Urban Science, 9(9), 335. https://doi.org/10.3390/urbansci9090335

[20] Swarup, D. J., Vidyasagar, S., Kalyanasundaram, V., Sujatha, A., Vijayakumar, A., and Sudhakar, M. (2025). AI-Powered Smart Traffic Management in Intelligent Transportation Systems. In Urban Mobility and Challenges of Intelligent Transportation Systems (pp. 51-70). IGI Global Scientific Publishing.

[21] Sarkar, S. R., and Tahura, S. (2025). AI-Enhanced Public Transportation Systems for Urban Sustainability. In AI and Emerging Technologies for Emergency Response and Smart Cities (pp. 97-116). IGI Global Scientific Publishing.

[22] Lukic Vujadinovic, V., Damnjanovic, A., Cakic, A., Petkovic, D. R., Prelevic, M., Pantovic, V., ... and Bodolo, I. (2024). AI-driven approach for enhancing sustainability in urban public transportation. Sustainability, 16(17), 7763.

[23] Adio, S. A., Sikhakhane-Nwokediegwu, Z., Erinjogunola, F. L., Ajirotutu, R. O., and Olayiwola, R. K. (2025). Integrating AI in Public Transport Workforces: A Review of HR Challenges and Opportunities.

[24] Khan, A., ur Rahman, S., Ullah, F., Khattak, M. I., Bait-Suwailam, M. M., and El Sayed, H. (2024). V2I-VTL: IoT-Enabled adaptive traffic light controller and emission reduction at intersection. PeerJ Computer Science, 10, e2507.

[25] Naeem, M. A., Chaudhary, S., and Meng, Y. (2024). Road to efficiency: V2v enabled intelligent transportation system. Electronics, 13(13), 2673.

[26] Silva, Ó., Cordera, R., González-González, E., and Nogués, S. (2022). Environmental impacts of autonomous vehicles: A review of the scientific literature. Science of The Total Environment, 830, 154615.

[27] Othman, K. (2022). Exploring the implications of autonomous vehicles: A comprehensive review. Innovative Infrastructure Solutions, 7(2), 165.

[28] Harsha, T. R., Bhat, V. P., Prabhanjan, K., Vinay, S. K., and Thomas, L. (2025). Graph Neural Networks for Scene Understanding: A Review and Future Directions. Graph Neural Networks: Essentials and Use Cases, 277-339.

[29] Binshaflout, E., Hamrouni, A., and Ghazzai, H. (2025). Graph Neural Networks for Vehicular Social Networks: Trends, Challenges, and Opportunities.

[30] Lakhouit, A. (2025). Revolutionizing urban solid waste management with AI and IoT: a review of smart solutions for waste collection, sorting, and recycling. Results in Engineering, 104018.

[31] KS, A., Bhadani, G., Ninawe, S. S., and Manjunath, T. C. (2025). Artificial Intelligence Applications in E-Waste Sorting and Recycling Processes. Grenze International Journal of Engineering and Technology (GIJET), 11.

[32] Okechukwu, I., Duru, N. N., and Ibe, K. (2025). Transforming Urban and Municipal Plastic Waste Management through Smart Technologies. SustainE, 3(4).

[33] Lakhouit, A. (2025). Revolutionizing urban solid waste management with AI and IoT: a review of smart solutions for waste collection, sorting, and recycling. Results in Engineering, 104018.

[34] Fatorachian, H., Kazemi, H., and Pawar, K. (2025). Digital technologies in food supply chain waste management: a case study on sustainable practices in smart cities. Sustainability, 17(5), 1996.

[35] Song, C., and Wu, Z. (2024). Artificial intelligence-assisted RFID tag-integrated multi-sensor for quality assessment and sensing. Sensors, 24(6), 1813.

[36] Yazan, D. M., van Capelleveen, G., and Fraccascia, L. (2022). Decision-support tools for smart transition to circular economy. In Smart Industry–Better Management (pp. 151-169). Emerald Publishing Limited.

[37] Grosso, C., and Fraccascia, L. (2024). Exploring The Potential Of Ai-Enhanced Toolkit For Products Co-Design In Industrial Symbiosis Dynamics. In XXXV Rsa Aiig How Ai Is Changing Economic Systems, Organizations, And Society (Pp. 383-397). Aiig Associazione Italiana Ingegneria Gestionale.

[38] Hossain, M., Al Aziz, R., Karmaker, C. L., Debnath, B., Bari, A. M., and Islam, A. R. M. T. (2024). Exploring the barriers to implement industrial symbiosis in the apparel manufacturing industry: Implications for sustainable development. Heliyon, 10(13).

[39] Enose Kamalabai, N., Hannola, L., and Donoghue, I. (2025). Role of Industrial Artificial Intelligence in Advancing Human-Centric Sustainable Development of Industry 5.0. In Contemporary Issues in Industry 5.0: Towards an AI Integrated Society (pp. 325-371). Cham: Springer Nature Switzerland.

[40] Alfahaid, A., Alalwany, E., Almars, A. M., Alharbi, F., Atlam, E., and Mahgoub, I. (2025). Machine Learning-Based Security Solutions for IoT Networks: A Comprehensive Survey. Sensors, 25(11), 3341.

[41] Veeraprasanth, A., Sriramnath, K., Suresh, P., and Elango, M. K. (2025, February). AI-Driven IoT System for Water Quality Assessment and Leakage Prevention. In 2025 4th International Conference on Sentiment Analysis and Deep Learning (ICSADL) (pp. 476-481). IEEE.

[42] Zou, S., Ju, H., and Zhang, J. (2025). Water Quality Management in the Age of AI: Applications, Challenges, and Prospects. Water, 17(11), 1641.

[43] Yasin, K. H., Yasin, M. I., Iguala, A. D., Gelete, T. B., Tulu, D., and Kebede, E. (2025). Predictive machine learning and geospatial modeling reveal PM10 hotspots and guide targeted air pollution interventions in Addis Ababa, Ethiopia. Discover Applied Sciences, 7(4), 263.

[44] Bhatia, S., Sachdeva, S., and Goswami, P. (2022). Air pollution prediction and hotspot detection using machine learning. Journal of Statistics and Management Systems, 25(7), 1553-1564.

[45] Fu, J., Tang, D., Grieneisen, M. L., Yang, F., Yang, J., Wu, G., ... and Zhan, Y. (2023). A machine learning-based approach for fusing measurements from standard sites, low-cost sensors, and satellite retrievals: Application to NO2 pollution hotspot identification. Atmospheric Environment, 302, 119756.

[46] Seelam, D. R., Kidiyur, M. D., Whig, P., Gupta, S. K., and Balantrapu, S. S. (2025). Integrating artificial intelligence in blue-green infrastructure: enhancing sustainability and resilience. In Integrating Blue-Green Infrastructure Into Urban Development (pp. 347-372). IGI Global Scientific Publishing.

[47] Wang, D., Xu, P. Y., An, B. W., and Guo, Q. P. (2024). Urban green infrastructure: Bridging biodiversity conservation and sustainable urban development through adaptive management approach. Frontiers in Ecology and Evolution, 12, 1440477.

[48] Omrany, H., and Al-Obaidi, K. M. (2024). Application of digital twin technology for Urban Heat Island mitigation: review and conceptual framework. Smart and Sustainable Built Environment.

[49] Riaz, K., McAfee, M., and Gharbia, S. S. (2023). Management of climate resilience: exploring the potential of digital twin technology, 3D city modelling, and early warning systems. Sensors, 23(5), 2659.

[50] Ficili, I., Giacobbe, M., Tricomi, G., and Puliafito, A. (2025). From sensors to data intelligence: Leveraging IoT, cloud, and edge computing with AI. Sensors, 25(6), 1763.

[51] Roostaei, J., Wager, Y. Z., Shi, W., Dittrich, T., Miller, C., and Gopalakrishnan, K. (2023). IoT-based edge computing (IoTEC) for improved environmental monitoring. Sustainable computing: informatics and systems, 38, 100870.

[52] Rito, P., Almeida, A., Figueiredo, A., Gomes, C., Teixeira, P., Rosmaninho, R., ... and De Carvalho, N. B. (2023). Aveiro tech city living lab: A communication, sensing, and computing platform for city environments. IEEE Internet of Things Journal, 10(15), 13489-13510.

[53] Koormala, H., Reddy, C. K. K., Balusa, V. S., Jillapalli, N., and Hanafiah, M. M. Enhancing urban safety: AI-driven security solutions for smart cities. In Information Security Governance using Artificial Intelligence of Things in Smart Environments (pp. 146-163). CRC Press.

[54] Alam, T. (2024). Data privacy and security in autonomous connected vehicles in smart city environment. Big Data and Cognitive Computing, 8(9), 95.

[55] Shafik, W. (2024). Ethical use of machine learning techniques in smart cities. In Ethical Artificial Intelligence in Power Electronics (pp. 21-47). CRC Press.

[56] Mashiat, T. (2024). Simulation to Practice: Data-Driven Characterization of Fairness in Societal Resource Allocation (Doctoral dissertation, George Mason University).

[57] Ntanda, A., and Carolissen, R. (2025). Technology's dual role in smart cities and social equality: A systematic literature. Journal of Local Government Research and Innovation, 6, 238.

[58] Clavijo, D. (2023). Older people and the smart city–Developing inclusive practices to protect and serve a vulnerable population. Internet policy review, 12(1).

[59] Bricout, J., Baker, P. M., Moon, N. W., and Sharma, B. (2021). Exploring the smart future of participation: Community, inclusivity, and people with disabilities. International Journal of E-Planning Research (IJEPR), 10(2), 94-108.

[60] Chen, Y. C., Ahn, M. J., and Wang, Y. F. (2023). Artificial intelligence and public values: value impacts and governance in the public sector. Sustainability, 15(6), 4796.

[61] Chaudhary, G. (2024). Unveiling the black box: Bringing algorithmic transparency to AI. Masaryk University Journal of Law and Technology, 18(1), 93-122.

[62] Dave, D. M. K., and Mittapally, B. K. (2024). Data integration and interoperability in IoT: challenges, strategies and future direction. Int. J. Comput. Eng. Technol.(IJCET), 15, 45-60.

[63] Bittencourt, J. C. N., Costa, D. G., Portugal, P., and Vasques, F. (2024). A survey on adaptive smart urban systems. IEEE Access.

[64] Hassan, A., Nizam-Uddin, N., Quddus, A., Hassan, S. R., Rehman, A. U., and Bharany, S. (2024). Navigating IoT Security: Insights into Architecture, Key Security Features, Attacks, Current Challenges and AI-Driven Solutions Shaping the Future of Connectivity. Computers, Materials and Continua, 81(3).

[65] Kolotouchkina, O., Ripoll González, L., and Belabas, W. (2024). Smart cities, digital inequalities, and the challenge of inclusion. Smart Cities, 7(6), 3355-3370.

[66] Shin, S. Y., Kim, D., and Chun, S. A. (2021). Digital divide in advanced smart city innovations. Sustainability, 13(7), 4076.

[67] Ali, H., and Fatima, T. (2025). Integrating Neural Networks and Symbolic Reasoning: A Neurosymbolic AI Approach for Decision-Making Systems.

[68] Bhuyan, B. P., Ramdane-Cherif, A., Tomar, R., and Singh, T. P. (2024). Neuro-symbolic artificial intelligence: a survey. Neural Computing and Applications, 36(21), 12809-12844.

[69] Attah, R. U., Garba, B. M. P., Gil-Ozoudeh, I., and Iwuanyanwu, O. (2024). Strategic partnerships for urban sustainability: Developing a conceptual framework for integrating technology in community-focused initiatives. GSC Adv Res Rev, 21(2), 409-18.

[70] Al-Raeei, M. (2024). Artificial intelligence for climate resilience: advancing sustainable goals in SDGs 11 and 13 and its relationship to pandemics. Discover Sustainability, 5(1), 513.