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AI-IoT Based Decision-Making Models for Smart Cities and Infrastructure

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Abstract: Smart city management and operations are being revolutionized by the confluence of AI and the IoT, which makes it possible to make data-driven, intelligent decisions in a variety of important urban domains. Traditional methods of governance and decision-making are becoming less and less effective in handling dynamic difficulties in areas like public safety, infrastructure, energy, and transportation as cities grow in size and complexity. This research presents a thorough evaluation of the decision-making models based on AI and IoT that are influencing the development of urban infrastructure. We start by reviewing the literature, then we compare approaches, contextualize current research trends, and pinpoint knowledge gaps in AI-IoT deployments. In order to fuel intelligent urban systems, the study then examines the fundamental elements and integration of AI & IoT approaches. To demonstrate how AI-IoT systems improve operational efficiency, responsiveness, and sustainability in industries like traffic control, healthcare, energy management, and emergency response, real-world applications and case studies are reviewed. Critical analysis is done on issues such interoperability, real-time restrictions, system scalability, and data privacy. As possible facilitators of more safe, resilient, and participatory urban ecosystems, new future directions such as edge AI, federated learning, digital twins, blockchain integration, and citizen-in-the-loop frameworks are examined. With this review, we hope to shed light on the revolutionary possibilities of AI-IoT systems while pointing out obstacles and possibilities for improving smart city decision-making.

Keywords: AI, IoT, Smart Cities, Machine Learning, Decision Making.

1. INTRODUCTION

The increased urbanization, resource constraints, environmental issues, and expectations of inhabitants with more access to technology have all contributed to the emergence of the idea of smart cities. Advanced data and communication technologies (ICTs), integrated systems, and intelligent services are used in smart cities to enhance operational efficiency, foster sustainable urban growth, & enhance the standard of life for its citizens (Silva et al., 2018). Physical and digital layers cohabit in interconnected ecosystems that have replaced the conventional city infrastructure, which was frequently divided and manually maintained, over the previous 20 years.

The development of intelligent infrastructure has been made possible by the major technical enablers, including edge devices, cloud computing, broadband connectivity, and real-time data analytics. These infrastructures include, among other things, intelligent energy grids, automated waste management, responsive healthcare networks, and smart transportation systems. Technology's ability to support educated, strategic, and real-time decision-making is becoming more and more important as cities strive to become more resilient, adaptable, and citizen-centric.

Modern urban settings are distinguished by their intricacy and vibrancy. In terms of energy, mobility, public safety, healthcare, water supply, and governance, cities are no longer static areas but rather dynamic systems with ever-changing demands. Numerous factors, including traffic patterns, economic activity, population density, climate, and citizen behaviour, all have an impact on these demands (Nederhand et al., 2023).

The use of conventional, reactive decision-making models to manage such complex systems results in underutilization of resources, delays, and inefficiencies. When properly recorded and analysed, real-time data can facilitate both long-term strategic planning and prompt interventions. In order to maximize urban services, forecast future requirements, and minimize infrastructure disruptions, data-driven DM is crucial. One of the fundamental requirements for any city hoping to become "smart" is the capacity to gather, analyse, and act upon enormous amounts of diverse urban data.

1.1. Integration of AI and IoT

As mentioned in (KaaIoT, 2025), AI and IoT are two revolutionary technologies that, when applied separately, have a significant positive impact on urban management. Through the deployment of a wide range of networked devices and sensors throughout infrastructure, IoT provides the sensory layer of smart cities. These gadgets continuously gather data from the physical world in real time, including temperature, pollution levels, traffic patterns, water and energy usage, and more. Raw data by itself, however, is insufficient to produce useful insights.

Here's where AI comes into play. Without human assistance, AI approaches like ML, DL and reinforcement learning are utilize to process the enormous amount of IoT data, identify trends, predict results, and make wise decisions. Predictive, autonomous, and adaptive urban systems are made possible by AI and IoT working together. In traffic management, for instance, IoT sensors identify patterns of congestion, and AI algorithms adjust traffic light timing or vehicle routing accordingly. Scalable and effective decision-making for intricate urban infrastructure systems is supported by this integration.

Figure 1. Illustration of an AI-IoT Enabled Smart City (IOT Smart Cities, 2024)

1.2. Scope and Objective

The goal of this review paper is to explore and critically analyse the part of AI-IoT based decision-making models in the growth & working of smart cities and intelligent infrastructure. Its objectives are to give a basic understanding of AI & IoT approaches in the terms of urban systems, analyse architectural frameworks that facilitate AI-IoT decision models, and categorize different AI-driven decision-making techniques that are combined with IoT. The study also examines and evaluates case studies and real-world applications in important urban areas like public safety, energy, transportation, healthcare, and environmental management. The implementation of these systems is also identified, with a particular emphasis on issues of scalability, interoperability, data privacy, energy efficiency, and AI trust. The review also identifies new research approaches, trends, and future directions for developing AI-IoT-powered smart cities. Even though the scope is wide, it stays concentrated on decision-making as the primary function made possible by the combination of AI and IoT, encompassing both theoretical underpinnings and real-world applications.

This paper is divided into seven sections to give readers a clear and structured understanding of the subject. The literature on AI-IoT systems in SC is reviewed in Section 2. The core ideas of AI & the IoT are explored in Section 3, along with how their combination serves as the technological foundation for intelligent urban infrastructure. In Section 4, real-world case studies and useful applications illustrate how AI-IoT is revolutionizing vital industries like public safety, healthcare, energy, and transportation. Section 5 outlines the major challenges and limitations associated with implementing AI-IoT decision-making systems, including issues of scalability, data privacy, interoperability, and public trust. Section 6 presents emerging research directions and technologies, such as edge

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AI, federated learning, digital twins, blockchain integration, and citizen-centric frameworks, which offer potential solutions to current limitations. Finally, Section 7 concludes the paper by summarizing the key findings and proposing a forward-looking roadmap for the continued development of AI-IoT-powered smart cities.

2. REVIEW OF LITERATURE

As the world's urban population is expected to reach 66% or 70% by 2050 (O'Dwyer et al., 2019), there are growing worries about the environmental as well as security implications. In response to this issue, smart cities based heavily on technology for ICTs have been suggested and implemented in a variety of countries. Smart cities combine multiple innovations, including the IoT, blockchain, AI, ML, and DRL, to create holistic services. A few existing works are discussed below.

Lifelo et al. (2024) investigates the integration of AI-powered Metaverse approaches for better urban planning, resource management, & citizen involvement. Authors explore major enabling technologies like digital twins, the IoT, blockchain, as well as their potential uses in smart infrastructure, virtual government, and environmental sustainability. Moreover, the paper discusses the major issues, including data privacy, interoperability, and energy consumption, and proposes future research directions for realizing intelligent, inclusive, as well as sustainable urban ecosystems. **Omaji Samuel et al. (2022)** A safe energy system based on blockchain is proposed for cars in sustainable cities & societies. The suggested approach provides car owners with a dynamic demand-focused pricing approach that takes into account vehicle types, demand times, as well as geographic areas. Based to the numerical evaluations, energy costs 89.23% less than under the MPPS, FPS, and time-of-use pricing scheme (ToU), which are 83.46%, 73.86%, and 53.07%, correspondingly. The proposed system has a security rating of 60.32%, compared to the MPPS system's 39.67%. **Lei Zhang et al. (2023)** demonstrates how the smart city leverages blockchain approach to secure transmission of data security. As a result, all of the subsystems in smart cities function together securely, which is what sparked the integrated organization in this architecture. The quality of the suggested approach could be seen by addressing the outcomes of simulations on a test system common to smart cities. **Jyothi et al. (2024)** seeks to address these issues by proposing the proposed AI-DMS for SC. The outcomes of simulations show that AI-DMS surpasses the other techniques. It has a DQS of 95.12% (training) as well as 93.76% (testing). The rate of 85.23% (training) as well as 82.76% (testing), a Processing Effectiveness of 90.54% (training) and 88.76% (testing), accuracy of 80.12% (training) as well as 78.45% (testing), as well as a Data Access Moments of 22.76 ms (training) &21.32 ms (testing). **Rosca et al. (2024)** suggests a PUTSS method for distributing a public urban transport fleet based on the set of passengers waiting for a bus while taking effectiveness into account. The method is embedded into a C#-based software program that simulates an actual scenario combining 2 public urban transportation vehicles. The overall accuracy rating of 89.81% illustrates the software's actual usability. **Palagan et al. (2025)** Implement decentralized waste collection schedule and edge computing for DM. Using an RF method, the system forecasts bin status with 99.25 % accuracy. Blockchain also contributed to a 95% increase in customer trust. **Latif et al. (2024)** proposed a new DL-based hybrid classification framework that merges LSTM with TAL to successfully forecast the direction of stock markets in smart cities. The suggested algorithm's prediction performance is contrasted to the standard models of CNN, LSTM, SVM, & RF utilizing assessment variables such as accuracy, precision, recall, F1-score, AUC-ROC, PR-AUC, & MCC. Numerical findings reveal that our suggested approach outperforms the benchmark algorithms on most assessment indicators and all databases. **Hammoumi et al. (2024)** intends to utilize AI to classify the efficiency of SC as well as discover the variables that contribute to their intelligence. Several ML algorithms, including RF, ANN, SVM, & GB, were tested to be contrasted to determine the best one. The outcomes revealed that RF & ANN are the best trained designs, with the highest levels of accuracy. **Ramkumar et al. (2024)** A revolutionary Intelligent Parking System (IPS) for Smart Cities is presented that will enhance large-scale urban parking management through the use of IoT & DL approaches. Using the database maintained by ImageNet and a three-layered DNN with CNNs for IP & RNNs for predictive analytics, it achieves a 95% accuracy rate in only 300 milliseconds of execution. **Priyadarshini et al. (2024)** proposed an innovative technique for detecting anomalies produced by IoT cyberattacks in SC. The study runs deep experiments with authentic databases from smart cities. The findings highlight the critical role that these strategies play in fortifying SC & encouraging the creation of adaptable & robust cybersecurity solutions in the IoT era. **Ahmad et al. (2024)** In the smart city surroundings, PES uses a Blockchain and Internet of Things Enabled Secure as well as Transparent Supply Chain Management structure. The system's efficiency is improved by fine-tuning the Queue design's variables using a RF-PO. **Binbusayyis et al. (2024)** planned smart city-based AQI estimation seeks to use the suggested regression technique in the data set which collects harmful pollutants on an hourly through daily basis from many Indian cities during 2015 and 2020. The suggested regression algorithm's performance is evaluated using metrics like MAE, MSE, R2, MAPE, and RMSE values of 0.1013, 0.0134, 0.9479, 0.1152, and 0.1156. **Abdulla et al. (2024)** offer an architecture for energy consumption forecasting based on adaptive learning, federated learning, or edge computing ideas. The results we obtain show that adaptive FL outperforms centralized learning while maintaining privacy, reducing

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communication overhead, cutting forecast error rate by 8%, & shortening training time by nearly 80%. Table 1 presents the current work in tabular form.

Table 1: Tabular form of existing work

References	Objective	Technology	Dataset/Tool	Drawbacks	Conclusion
Huang et al.,(2022)	Authentication for Smart City	Unified blockchain	Urban sensor data	scalability	Achieve all desirable security and privacy properties
Lei Zhang et al.,(2023)	To handle the operational uncertainties of the transportation systems	Blockchain technology	MATLAB	Lack of privacy of data shared on the network	Typical smart city test system to show the quality of the proposed model.
Ramkumar et al.(2024)	Intelligent Parking System for Smart Cities	Deep Learning	ImageNet database	Unable to operate a deeper integration with controlled vehicles, greater interoperability with other smart city components .	Accuracy = 95%
Palagan et al.(2025)	Predictive analysis of sustainable waste management in smart cities	IoT & Blockchain	Real-time sensor data	Scalability concerns	Accuracy of Random Forest =99.25 % , Blockchain technology=95%
Jyothi et al.(2024)	Management System for Smart Cities	Artificial Intelligence	10,000 data points/ MATLAB	Scalability & Long-Term Maintenance	Accuracy =80.12%
Rosca et al.(2024)	Designing and implementing	PUTSS algorithm	C# simulator	Data Availability and Quality	Accuracy rate = 89.81%
Latif et al.(2024)	Improved forecasting of stock markets	DL	U.S., U.K., China & India, from 2005 to 2022	Limited Explainability	Accuracy= 96%
Priyadarshini et al. (2024)	Anomaly Prediction of IoT Cyberattacks in SC	Federated & split learning	NSL-KDD & UNSW-NB1 Datasets	Increased System Complexity	Federated Learning=97.78, Split Learning=98.02
Binbusayyis et al. (2024)	Prediction of air quality index in smart city	Deep learning approach	Air- Quality-Data from multiple cities of india	lack of external validation	Root Mean Square Error) = 0.1156

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3. FUNDAMENTALS OF AI & IoT

The foundation of any smart city is its capacity to sense its surroundings, analyse vast amounts of data in real time, and react with automated, well-informed decisions. IoT and AI, two interrelated technologies, are the main forces behind this capability. Through extensive networks of devices and sensors, IoT allows cities to sense and gather data; however, artificial intelligence provides the computational intelligence needed to interpret this data and make decisions. In order to set the stage for how their integration aids in decision-making in smart city ecosystems, this section offers a thorough understanding of both technologies.

3.1. Artificial Intelligence

AI is the replication of human cognition in robots that can execute activities that typically call for human cognition, including learning, reasoning, thinking, or language comprehension (Staff, 2025). The field of AI has evolved significantly over the past few decades from early symbolic logic and rule-based expert systems to modern data-driven approaches like ML & DL. Initially, AI systems were rule-based and relied heavily on human-defined logic to perform specific tasks (e.g., expert systems in the 1980s and 1990s). However, the emergence of large-scale data, increased computational power, and algorithmic innovations have given rise to data-centric AI models that can learn patterns from data rather than being explicitly programmed. This evolution has shifted AI from narrow task-specific applications to more generalized and adaptive systems.

3.1.1. Categories of AI in Smart Cities

Machine Learning (ML): A subset of AI that uses statistical approaches to enhance machines efficacy on a task via practice. ML designs are largely utilized in predictive analytics, traffic flow forecasting, and anomaly detection in urban infrastructure.

DL: A specialized form of ML based on ANN with many phases. DL is particularly effective in tasks involving image recognition (e.g., video surveillance), speech processing (e.g., voice-controlled systems), and high-dimensional data analysis.

NLP: NLP enables AI systems to perceive, interpret, or create natural language. In smart cities, it enables intelligent chatbots, voice assistants for public services, and sentiment analysis of citizen feedback.

Expert Systems: These are rule-based systems designed to emulate the decision-making abilities of human experts. Though less adaptive than ML, they are still used in structured decision environments like water management systems or regulatory compliance checking.

3.1.2. AI in Urban Analytics, Prediction, and Automation

AI is essential to smart cities because it helps turn unprocessed urban data into useful information by allowing urban analytics to comprehend resource usage, service demand, and population behaviour. It enables authorities to make plans in advance by supporting predictive modelling to forecast pollution levels, energy consumption peaks, and traffic congestion. Also, AI makes it easier to automate important tasks like emergency response management, energy distribution, traffic light control, and public transportation routing. This change in governance from reactive to proactive and predictive greatly improves urban systems' sustainability, responsiveness, and efficiency.

3.2. IoT

The system of physical objects devices, sensors, cars, buildings, & other embedded systems that are online and have the ability to collect & share data is known as the IoT. IoT functions as the sensory system that records the city's pulse in real time within the framework of smart cities.

Sensor networks, which are distributed collections of sensing devices that collect data on variables like temperature, air quality, traffic flow, water levels, electricity usage, and movement, are at the core of Internet of Things systems. These sensors are frequently placed throughout public areas, buildings, roads, transit systems, and utility grids.

Edge computing is becoming more and more popular as a way to handle the massive amount of information produced by these sensors. Instead of sending all data to centralized servers or cloud systems, edge computing contains processing data close to the source, or at the "edge" of the system. This method minimizes network congestion, improves real-time responsiveness, and lowers latency all of which are essential for making snap decisions like traffic redirection or accident detection.

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City systems can be responsive and situationally aware thanks to real-time data collection. Smart waste bins optimize garbage collection routes by sending alerts when they are full, just as smart parking systems use IoT sensors to identify empty spots and alert drivers via apps.

3.2.1. IoT Architecture in Urban Infrastructure

IoT systems in smart cities are typically organized into three functional layers:

Perception Layer (Sensing Layer): This includes all physical devices and sensors that perceive environmental data such as temperature sensors, cameras, GPS modules, water flow meters, and pollution detectors.

Network Layer: Responsible for transmitting data collected by sensors to data centres or edge nodes. This layer includes interaction approaches like Wi-Fi, 5G, Zigbee, Lora WAN, & NB-IoT, depending on the use case and range/bandwidth requirements.

Application Layer: This is where data is analysed, visualized, and converted into actionable insights. It includes dashboards for city planners, mobile apps for citizens, control systems for utilities, and APIs for third-party service providers.

Through this layered architecture, IoT enables end-to-end connectivity and intelligence, providing the foundational data required for AI algorithms to function effectively.

4. APPLICATIONS AND CASE STUDIES

The convergence of AI and IoT is transforming urban systems in a number of fields. Applications in the real world show how revolutionary these technologies are in facilitating automated, intelligent, and data-driven decision-making. The main application areas and case studies that demonstrate how AI-IoT models are actively changing city operations and improving urban quality of life are highlighted in this section.

4.1 Smart Traffic

Traffic and mobility management is one of the most well-known areas of AI-IoT applications. Cities are improving their urban transportation systems by combining AI algorithms with actual-time sensor information (from GPS, traffic cameras, & IoT devices embedded in roads). By using artificial intelligence (AI) to modify traffic signal timings in real time, predictive traffic signal control, like that found in Surtrac (Pittsburgh, USA), can cut travel time by up to 25% and idle time by more than 40% (Simek, 2022).

IoT-based traffic flow sensors and AI-driven analytics are used by congestion control systems, such as those in Barcelona, to reroute cars and steer clear of densely populated areas. Waymo (USA) (Ali et al., 2024; Hu et al., 2023) and Autonom Cab (France) are two examples of autonomous vehicle coordination projects that use AI for navigation and rely on IoT-enabled infrastructure, such as roadside units (RSUs) and smart traffic lights, for safe operation.

4.2 Smart Energy Management

Through load balancing, demand forecasting, and smart grid technologies, AI-IoT systems are essential to optimizing urban energy consumption. Utility companies can effectively manage supply by using AI models to analyse weather data, smart meters, and Internet of Things sensors to predict designs in energy demand. By integrating RES like solar & wind and balancing loads, the Amsterdam Smart City project uses AI to automate energy usage in residences and public houses(Putra and Van Der Knaap, 2019). IoT and deep learning are used in South Korea's Smart Grid (Singh et al., 2025) project to monitor electricity consumption in real time and perform predictive analytics, which helps to lower peak demand and improve sustainability. In addition to improving efficiency, these systems lower citizens' energy expenses and greenhouse gas emissions.

4.3. Infrastructure Monitoring

The structural health of urban infrastructure, including buildings, bridges, roads, and railroads, is frequently monitored by AI-IoT systems. Artificial intelligence (AI) algorithms can detect irregularities that might point to structural fatigue or damage by implementing sensor networks that continuously gather data on vibration, pressure, and material strain. The Stonecutters Bridge in Hong Kong, for example, employs an IoT-based monitoring system that uses AI-based anomaly detection to guarantee prompt maintenance and avert mishaps (Wang et al., 2023). Similar to this, the USA's Smart Roadway Systems (Hossein et al., 2024) incorporate sensors into pavement to track vehicle weight and surface condition, enhancing road safety and maintenance planning. These uses show how AI-IoT can improve critical infrastructure's robustness and dependability.

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4.4. Public Safety and Surveillance

AI and IoT are utilized in the field of public safety to create automated emergency response systems and proactive surveillance systems. Large-scale CCTV camera networks with AI-based facial recognition and behavior detection algorithms have been installed in cities like Chicago and London. These cameras are able to detect suspicious activity in real time (Fontes et al., 2022). Furthermore, law enforcement organizations receive real-time information about incidents from IoT-based alert systems like gunshot detection (e.g., ShotSpotter in the USA), which facilitates a quicker response (Khan, 2025). City officials can better allocate resources and enhance community safety by integrating these systems with AI-powered dashboards for crime pattern analysis.

4.5. Environmental Monitoring

Smart cities place a lot of emphasis on environmental sustainability, and AI-IoT technologies are being used for smart agriculture, waste management, and pollution monitoring. For instance, India's Delhi and Bengaluru have put in place air quality monitoring systems that track pollution levels and predict smog events using IoT sensors and machine learning, enabling authorities to promptly issue health warnings (Rautela and Goyal, 2024). In order to optimize waste collection paths & minimize fuel usage, smart waste bins (Bojic, 2025), like those found in Copenhagen, are equipped with sensors that alert municipal services when they need to be emptied. In order to conserve water and boost yield, smart irrigation systems in California and Israel use weather information, soil moisture sensors, and AI algorithms to deliver the appropriate set of water at the right time (Mag, 2025).

Table 2: Application Areas and Case Studies of AI-IoT Integration in Smart Cities

Application Area	Key Technologies	Case Studies / Cities	Impact	Reference
Smart Traffic	• AI-based predictive traffic control • IoT sensors (GPS, cameras, RSUs) • Real-time data	• *Surtrac, Pittsburgh*: Adaptive signal timing • *Barcelona*: AI-driven congestion rerouting • *Waymo (USA), Autonom Cab (France)*: AV coordination	• Travel time ↓ 25%, Idling ↓ 40% • Real-time congestion avoidance • Safe autonomous navigation	Simek (2022); Ali et al. (2024); Hu et al. (2023)
Smart Energy Management	• Smart meters, IoT devices • AI for load forecasting • Renewable energy integration	• *Amsterdam Smart City*: AI load balancing • *South Korea*: Deep learning in smart grid	• Efficient energy usage • Peak demand reduction • Cost savings & emission reduction	Putra and Van Der Knaap (2019); Singh et al. (2025)
Infrastructure Monitoring	• Structural sensors (vibration, strain) • AI anomaly detection • Predictive maintenance	• *Stonecutters Bridge, Hong Kong*: AI-based health monitoring • *USA Smart Roads*: Sensor-embedded pavements	• Early fault detection • Extended infrastructure life • Optimized maintenance scheduling	Wang et al. (2023); Hossein et al. (2024)
Public Safety & Surveillance	• AI facial/behavior recognition • IoT alert systems (e.g., gunshot detection) • Real-time data analysis	• *Chicago & London*: CCTV with AI analytics • *ShotSpotter (USA)*: Gunshot detection	• Crime prediction & prevention • Faster emergency response • Data-informed policing	Fontes et al. (2022); Khan (2025)
Environmental Monitoring	• IoT sensors for air, waste, and soil • ML for forecasting	• *Delhi & Bengaluru*: Air quality forecasting	• Pollution alerts Efficient waste collection	Rautela and Goyal (2024); Bojic (2025); Mag (2025)

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	• AI-driven automation	• *Copenhagen*: Smart waste bins • *Israel & California*: Smart irrigation	• Water conservation & crop yield improvement

Table 2 summarizes a variety of applications and case studies that demonstrate the substantial potential of AI-IoT systems in creating smart cities that are resilient, responsive, and sustainable. These technologies serve as the basis for next-generation urban governance, which includes everything from energy conservation and traffic flow management to environmental protection and safety. Continuous innovation, policy alignment, and the ethical application of AI will be essential for long-term success as more cities implement and scale these solutions.

5. CHALLENGES

Although AI-IoT technologies hold great promise for transforming smart city infrastructure, their widespread adoption, efficacy, and public acceptance are hampered by a number of significant issues and constraints. These problems cut across the technical, moral, financial, and operational spheres, and they frequently call for multi-stakeholder cooperation and flexible policy frameworks to resolve. This section addresses the most important challenges for integrating AI and IoT in urban settings.

5.1. Data Privacy & Security

In SC, AI-IoT systems depend on ongoing data collection from the environment, infrastructure, and residents. Sensitive personal information like location, behavior, medical records, energy use, surveillance footage, and more is included in this. This massive data collection can result in major privacy violations, illegal surveillance, and possible misuse if robust data governance frameworks are not in place. Furthermore, cybersecurity risks like data breaches, hacking, spoofing, and denial-of-service (DoS) attacks are inherent to IoT networks. For instance, a breach in a surveillance system or smart grid could have a domino effect on public safety. Therefore, to guarantee data protection, adherence to legal requirements (such as the GDPR), and public trust, encryption, secure communication protocols, decentralized data storage (like blockchain), and stringent access controls are crucial.

5.2. Scalability of Models at the Urban Scale

Scalability is one of the largest technical challenges because smart cities produce terabytes of data every day. It is very difficult to maintain the same accuracy, latency, and efficiency across a whole city with millions of sensors, even though AI models might work well on small-scale prototypes or pilot projects. With scale come problems like processing lag, network congestion, and the requirement for substantial computational resources. Furthermore, not all municipalities, particularly those in developing nations, may be able to afford the substantial infrastructure (such as GPUs and cloud computing) needed to train sophisticated AI models like deep neural networks. Long-term sustainability requires that AI-IoT solutions be scalable both horizontally and vertically, meaning they can expand without breaking.

5.3. Real-Time Constraints

Urban systems that require real-time or nearly real-time decision-making include power grid management, emergency response, and traffic control. AI-IoT workflows, however, are multi-step, starting with the collection of sensor data and continuing through preprocessing, cloud transmission, AI inference, and actuation. Inefficiencies in the system, safety hazards, or delayed responses can result from delays at any point, particularly when caused by cloud computing latency or bandwidth constraints. For example, a delayed traffic signal update may result in accidents or gridlock. Lightweight AI models and EC, or processing information closer to the source, are becoming more and more important in order to meet real-time constraints. Nevertheless, there are still operational and technical difficulties in creating such low-latency, decentralized architectures.

5.4. Interoperability Among Heterogeneous Devices

Heterogeneous devices and systems constructed by various vendors utilizing various platforms, data formats, and communication protocols make up a typical smart city ecosystem. For AI-IoT systems to work together, smooth interoperability between these elements is essential. Data silos, misunderstandings between subsystems, and the failure of integrated applications can all be caused by a lack of standardization. For instance, the smart benefit is negated if a waste management sensor is unable to connect to a city's centralized dashboard because of a protocol mismatch. In order to address this, open standards, middleware platforms, APIs, and collaborative industry practices must be developed and adopted. A further aspect of interoperability is integration with legacy infrastructure, which might not be able to accommodate contemporary technologies.

5.5. Explainability and Trust in AI Models

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Deep learning systems in particular are frequently referred to as "black boxes" because they make predictions or make decisions without providing an explanation. This lack of explainability can cause mistrust, public opposition, and ethical issues in smart city applications that have an impact on daily life, like automated surveillance, healthcare triage, or law enforcement agencies. Furthermore, decisions made by AI that are biased or opaque may promote social injustices (e.g., discriminatory policing or resource allocation). Explainable AI (XAI) mechanisms must therefore be integrated in order to promote accountability and trust among stakeholders, including developers, legislators, and citizens. In technologies that interact with the public, transparency is not only a technical objective but also a social requirement.

5.6. Energy and Cost Constraints in IoT Devices

Many IoT devices are made to be inexpensive, low-power, and frequently run on batteries in challenging-to-reach or distant locations. Even lightweight models that incorporate AI processing capabilities, however, result in increased heat production, energy consumption, and hardware complexity. Moreover, continuous data transfer quickly depletes power. These limitations restrict the AI-IoT deployments' operational lifespan and cost-effectiveness. Smaller towns and rural areas might not be able to afford the substantial initial setup and upkeep costs associated with smart infrastructure, which includes sensors, gateways, edge devices, and connectivity. Overcoming this obstacle requires government subsidies or public-private partnerships, model optimization, and energy-efficient hardware design.

Although AI-IoT integration has many advantages for smart cities, there are challenges in putting it into practice. Cities must manage a complicated web of ethical and technical issues, ranging from safeguarding personal information and scaling systems to guaranteeing real-time performance, device interoperability, explainability, and cost-efficiency. A comprehensive approach that incorporates technological innovation, policy regulation, ethical standards, stakeholder engagement, and ongoing monitoring is needed to address these issues. Cities can only fully realize the transformative potential of AI and IoT for sustainable urban futures by addressing these issues head-on.

6. FUTURE TRENDS

There is a growing need to address current issues while investigating cutting-edge, future-ready technologies and frameworks as AI-IoT ecosystems and smart cities develop. Some of the most promising areas for future research are listed below, where developments could greatly improve the effectiveness, scalability, intelligence, and inclusivity of decision-making systems in urban settings.

6.1. Federated Learning in Smart cities

FL is a potential ML method that allows algorithms to be trained across several decentralized gadgets or nodes without transferring the initial data to a central server. In the terms of SC where vast amounts of information are continuously created by edge approaches like traffic cameras, smart meters, and public kiosks—FL (Yurdem et al., 2024) provides significant advantages. It preserves user privacy by keeping sensitive data like health or location information on local devices, aligning with data protection regulations such as GDPR. It also reduces bandwidth usage since only model updates, not raw data, are transmitted, which lightens the load on communication networks. Additionally, FL enables scalable and context-aware AI by allowing models to adapt to local patterns across different urban zones. For the future, research should focus on integrating FL with low-power IoT devices, securing the aggregation of distributed model updates, and addressing critical issues such as model drift, communication overhead, and fairness in multi-node collaborative training environments.

6.2. Digital Twins for Infrastructure Simulation

Digital Twins are dynamic virtual models of physical assets, processes, or entire urban devices that enable real-time tracking, simulation, & predictive analysis in smart cities. They can replicate and simulate various urban components such as traffic systems to predict congestion and optimize routes, energy grids to forecast peak demand, and infrastructure like bridges or buildings to monitor structural health over time. When integrated with AI, IoT, and continuous data streams, digital twins empower decision-makers with tools for proactive maintenance, cost-efficient interventions, and "what-if" scenario testing. For example, urban planners can evaluate the effects of proposed road construction on city traffic through digital simulations before physical work begins. Future research should focus on developing scalable and interoperable digital twin platforms capable of actual-time synchronization with diverse city datasets, incorporating immersive technologies like VR/AR for enhanced visualization, and enabling autonomous updates in response to changes in the physical environment.

6.3. Edge AI Models

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Most traditional AI models are computationally heavy and dependent on cloud infrastructure, making them unsuitable for the real-time, low-latency demands of smart city environments, which often operate under resource constraints. To address this, Edge AI (Samara, 2025) where AI algorithms are deployed directly on edge devices like sensors, gateways, and cameras—has emerged as a critical solution. Future research should focus on developing lightweight deep learning models capable of running on low-power microcontrollers, using optimization techniques like model quantization, pruning, & knowledge distillation to minimize energy consumption & model size. Additionally, creating edge-specific training frameworks to support distributed learning across the urban infrastructure will be essential. Advancing Edge AI will significantly improve the speed, reliability, privacy, and resilience of smart city systems, particularly in areas with limited or unreliable cloud connectivity.

6.4. Blockchain + AI-IoT for Secure Decision-Making

The combination of blockchain approach with AI-IoT devices holds essential promise for improving the security, transparency, & trustworthiness of decision-making processes in smart cities (Cointelegraph, 2025). Potential applications include maintaining immutable records of AI-generated decisions in domains such as law enforcement and utility management, enabling decentralized identity management for citizens accessing urban services, and using smart contracts to automate the enforcement of service-level agreements—for instance, triggering water supply adjustments based on sensor inputs. Additionally, blockchain provides auditability and accountability for public data usage and facilitates secure data sharing among untrusted entities, such as between different government departments or in public-private collaborations, without compromising data integrity. However, future research must address key challenges related to the scalability, energy consumption, and latency of blockchain networks and explore methods to integrate them seamlessly with real-time AI-IoT systems while maintaining high performance and responsiveness (B. U. I. Khan et al., 2024).

6.5. Citizen-in-the-Loop Systems

Smart cities must move beyond mere automation and efficiency to actively involve citizens in decision-making. The concept of Citizen-in-the-Loop (CITL) (Ponti, 2020) AI emphasizes the integration of citizen feedback, preferences, and ethical considerations into algorithmic processes, fostering more inclusive and people-centric urban systems. Examples of CITL approaches in smart cities include crowdsourced reporting platforms for civic issues such as potholes and streetlight outages, feedback-driven urban planning tools that adapt based on community preferences, and participatory budgeting systems powered by AI to allocate resources more fairly. Future research in this area can focus on developing user-friendly interfaces and intelligent algorithms that integrate citizen input in real-time, ensure representational fairness across diverse populations, and minimize algorithmic bias. By actively consisting citizens in DM, CITL approaches have the potential to enhance public trust, transparency, and accountability in AI-driven urban governance.

6.6. Cross-Domain Integration

Urban systems are inherently interconnected — for example, poor air quality (environment) affects public health, and traffic congestion influences emergency response times. Therefore, future AI-IoT research must focus on cross-domain integration, moving from siloed applications toward interoperable, holistic intelligence.

The key examples of cross-domain integration in smart cities include the co-optimization of traffic flow and ambulance routing during emergencies to ensure faster response times and save lives, as well as the use of predictive analytics that link pollution levels with spikes in respiratory illnesses, enabling proactive healthcare interventions. Additionally, energy-aware healthcare facilities can dynamically adjust their energy consumption based on real-time citywide grid conditions to ensure both efficiency and sustainability. Achieving such integration requires the development of unified data models, standardized communication protocols across domains, and multimodal AI systems capable of simultaneously processing diverse datasets such as mobility, health, and environmental data.

The future of AI-IoT in SC is rich with multidisciplinary opportunities and challenges. From decentralized learning and real-time edge intelligence to secure blockchain integration and citizen engagement, these directions push toward intelligent, inclusive, and resilient urban ecosystems. Advancing research in these areas will require collaboration among computer scientists, urban planners, policymakers, and civil society, ensuring that smart city technologies serve not just efficiency goals but also human and ethical values.

7. CONCLUSION

With the increasing demands of complex infrastructure, resource scarcity, and population growth on urban environments, integrating AI and IoT becomes more than just a technological fad; it becomes a strategic necessity.

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In order to redefine decision-making in smart cities, this paper has described the important role that AI-IoT systems play in moving away from reactive, human-dependent methods and toward proactive, autonomous, and data-driven mechanisms. The paper explores basic technologies, reviewed recent research, and cited practical applications where AI-IoT integration has resulted in observable gains in productivity, security, and service quality.

The future trends highlight the shift to AI-IoT models that are more decentralized, secure, and citizen-focused. Emerging ideas like digital twins, edge AI, federated learning, and blockchain-backed systems are more than just technological advances; they signify a change toward more transparent, sustainable, and inclusive urban governance. For smart city ecosystems to be trust-driven and participatory, it is equally important to acknowledge citizens as active participants in the decision-making process.

In summary, the intelligent coordination of infrastructure, data, and human values is what will ultimately determine the future of SC. The potential of AI-IoT-powered urban systems where cities not only operate effectively but also adapt, learn, and change in tandem with the demands of their residents and the environment will be fully realized through continued interdisciplinary cooperation and innovation, as this paper promotes.

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