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A Review of Adaptive Multi-Sensor Grids in IoT-Enabled Smart City Development

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Abstract: Rapid urbanization and continuous technological growth have increased the demand for sustainable and intelligent city infrastructures. Smart cities use the Internet of Things (IoT) and adaptive multi-sensor grids to improve resource management and real-time monitoring. This study examines how IoT-based adaptive sensor grids can improve the sustainability, resilience, and intelligence of future cities. It also highlights major innovations, current applications, and the challenges involved in implementing these systems. The authors conducted a systematic literature review using academic databases. The study analyzed research papers published between 2020 and 2025 using keywords such as "smart city," "IoT," and "multi-sensor grid." The findings show that adaptive sensor grids are central to smart city infrastructure. These grids continuously monitor traffic flow, energy consumption, air quality, and public health conditions. When combined with Artificial Intelligence (AI), they support real-time decision-making. This enables predictive energy management, dynamic traffic control, and efficient waste handling. Despite these benefits, several challenges remain. Major concerns include cybersecurity risks, data privacy issues, and a lack of interoperability between systems. Overall, adaptive multi-sensor grids play a crucial role in shaping sustainable and human-centered smart cities. To achieve this vision, it is essential to develop open standards, secure data frameworks, and strong governance policies. These steps ensure that IoT-driven urban systems remain safe, resilient, and fair for all citizens. Unlike conventional IoT sensor networks that mainly focus on data acquisition from isolated devices, adaptive multi-sensor grids integrate heterogeneous sensing systems with dynamic decision-making, context-aware sensing, AI-driven data fusion, and scalable communication architectures. The "adaptive" nature refers to the system's ability to modify sensing frequency, resource allocation, routing, and processing strategies based on environmental conditions, traffic load, energy availability, and application demands.

Keywords: Adaptive multi-sensor grids; smart cities; Internet of Things (IoT); sensor fusion; edge computing

1. Introduction

The concept of smart cities has emerged as a transformative framework for addressing urbanization challenges, optimizing resources, and promoting sustainability. A smart city is characterized by its ability to leverage advanced

technologies such as the Internet of Things (IoT), artificial intelligence (AI), and big data analytics to improve service delivery, enhance citizen's quality of life, and foster sustainable urban growth [1]. Unlike conventional urban systems, which are reactive and often fragmented, smart cities are proactive, data-driven, and adaptive [2]. Adaptive systems lie at the heart of this transformation, enabling urban infrastructure to respond dynamically to evolving conditions such as population surges, traffic congestion, or energy demand fluctuations [3]. When embedded in urban planning and operations, adaptive systems integrate real-time data streams from diverse sources, including transportation networks, energy grids, water systems, healthcare facilities, and public safety institutions, to support responsive and predictive governance. For instance, adaptive traffic systems can modify signal timings in real time based on traffic density, while adaptive energy systems can dynamically balance grid loads and promote renewable energy use [4]. By moving from static planning models to adaptive frameworks, cities can enhance resilience, sustainability, and efficiency [5].

The Internet of Things plays a pivotal role in the smart city vision. As the nervous system of a smart city, IoT encompasses a network of devices and sensors that collect, transmit, and interpret data in real time [6]. It enables real-time monitoring, decision-making, and optimization across the full range of urban management sectors, such as mobility, energy, the environment, and security [7]. Smart city applications demonstrate IoT's transformative potential across multiple urban domains. In smart mobility, sensors embedded in vehicles, roadways, and traffic infrastructure generate continuous data streams that help optimize traffic flow, reduce congestion, and lower overall emissions, contributing to more sustainable urban transport [8]. Smart energy systems rely on IoT-enabled grids and smart meters to balance supply and demand, facilitate the integration of renewable energy sources, and provide consumers with real-time feedback to manage energy use more efficiently [9]. In intelligent waste management, sensor-enabled bins identify fill levels and report collection requirements, enabling optimized routes that reduce fuel use, costs, and environmental footprints [10]. Intelligent health harnesses wearable technologies and Internet of Things monitoring platforms to enhance remote patient care, reduce hospital workloads, and shift toward preventive health management [11]. Finally, IoT applications fortify intelligent administration and security by facilitating transparent decision-making and active citizen engagement. These systems also enhance civic security through surveillance networks and instantaneous warning mechanisms [12]. In aggregate, applications show how Internet of Things-based solutions drive efficiency, sustainability, and a higher urban quality of life [13]. By connecting citizens, infrastructure, and administration platforms, the Internet of Things enables sustainable and equitable cities. As depicted in Figure 1, intelligent urban multi-sensor platforms integrate intelligent street lighting, intelligent transportation, waste-monitoring bins, water management platforms, fire alarms, charging stations, and other systems as intertwined networks that support sustainable urban administration [14].

Urbanization continues at an unprecedented pace, with estimates suggesting that nearly 70% of the global population will reside in cities by 2050 [15]. This rapid expansion strains existing infrastructure and creates significant challenges related to traffic, energy, the environment, waste disposal, and public safety [16]. Contemporary urbanization also presents an array of urgent challenges for smart city development. Traffic congestion is the most evident issue, as increasing vehicle numbers lead to longer journey times, higher fuel use, more pollution, and, consequently, decreased economic productivity [17]. In addition to mobility challenges, energy requirements present another important issue, as cities alone consume almost two-thirds of the planet's energy supply, placing enormous stress on the grid and driving greenhouse emissions [18]. Environmental imperatives add further complexity, as urban mobility and industrial development reduce atmospheric and aquatic quality, threatening public health and ecological balance [19]. Moreover, waste management grows more complex as larger urbanized communities produce higher volumes of waste, requiring more efficient recycling, collection, and disposal mechanisms, not only to reduce environmental degradation but also to manage rising costs [20]. Lastly, safety and security issues increase exponentially as cities continue to expand, as denser groups of people within urban areas become increasingly susceptible to crime, accidents, and disruptions from artificial and natural disasters [21]. Taken together, these challenges underscore the need for flexible, technology-based systems that facilitate sustainable and resilient urban life [22].

Adaptive multi-sensory grids constitute an integrated solution by combining different sensing technologies: air quality sensors, cameras for surveillance, RFID (Radio Frequency Identification) tags, GPS (Global Positioning System) devices, and mobile platforms under a single paradigm [23]. Such grids gather disparate data streams and convert them into actionable intelligence. In the context of smart city infrastructure, combining IoT and multi-sensor management enables responsive and efficient urban management. For example, transportation hubs use vehicle GPS data combined with feeds from CCTV cameras to monitor current traffic conditions and execute dynamic rerouting measures [24]. Similarly, environmental sensors distributed throughout urban areas continuously monitor air quality and pollutant levels and automatically trigger actions by authorities when hazardous situations occur, facilitating timely intervention and protecting public health [25]. Utility systems also use IoT-enabled smart meters to monitor energy consumption patterns, identify potential overload, and optimize resources. Beyond reducing energy waste, this also enables the development of more sustainable and resilient power infrastructure [26].

The motivation for studying adaptive IoT-enabled smart city systems stems from the urgent need to address mounting urban challenges while advancing sustainable development goals [27]. However, despite rapid progress, significant gaps persist. Smart city development is guided by objectives that go beyond technological advancement, focusing instead on building sustainable and inclusive urban ecosystems. A key goal is to promote urban resilience, ensuring cities are better equipped to withstand and recover from shocks such as natural disasters, infrastructure failures, or cyber-attacks [28]. By embedding adaptive systems and secure digital networks, cities can minimize disruptions and protect critical services. Equally important is the drive to advance sustainability, which involves reducing greenhouse gas emissions, conserving natural resources, and accelerating the adoption of renewable energy sources [29]. Through smart grids, intelligent transportation, and efficient waste management, cities can significantly lower their environmental footprint[30]. At the same time, smart city initiatives aim to enhance citizen well-being by improving access to services, strengthening safety measures, and fostering inclusivity in urban development[31]. Collectively, these goals highlight how adaptive, IoT-driven systems can create cities that are not only technologically advanced but also resilient, sustainable, and people-centered.

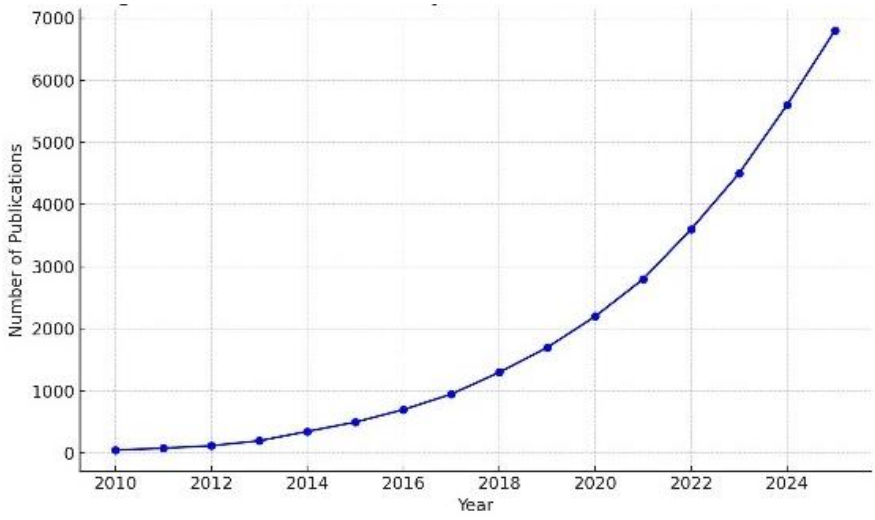


Figure 1. Growth of Smart City Research Publications (2010–2025)

Figure 1 illustrates the exponential rise in smart city research, underscoring the growing global focus on sustainable, technology-driven urban solutions. This growth reflects the growing need for adaptive, IoT-based systems. The deployment of IoT-enabled smart city systems faces several challenges that hinder their large-scale adoption and effectiveness. One major issue is integration, as many IoT platforms and devices function in isolated silos, preventing seamless communication and reducing overall efficiency [32]. Closely linked is scalability, since solutions that perform well in small pilot projects often encounter technical and operational difficulties when expanded to cover entire cities [33]. Another critical concern is security and

privacy, as the vast amount of personal and sensitive data collected by IoT devices raises risks of cyberattacks, data breaches, and misuse that can erode public trust [34]. Cost barriers also play a significant role, as the infrastructure, deployment, and ongoing maintenance of advanced IoT systems require substantial financial investments, making them difficult to implement in resource-constrained regions or developing nations [35]. Finally, the lack of standardization across devices, protocols, and platforms creates interoperability issues, preventing smooth integration of different technologies and limiting the scalability of smart city ecosystems [36]. Overcoming these gaps requires interdisciplinary approaches that merge technological, social, and governance perspectives [37]. Unlike conventional review studies that primarily summarize IoT applications in domains such as transportation, energy, waste management, and healthcare, this review critically synthesizes adaptive multi-sensor grid architectures for smart cities. The review focuses not only on application-level implementations but also on the evolution of intelligent urban sensing infrastructures through the integration of Artificial Intelligence (AI), edge and fog computing, sensor fusion, blockchain, federated learning, and adaptive communication frameworks. Furthermore, this study critically examines unresolved challenges related to interoperability, scalability, low-latency processing, cybersecurity, privacy preservation, and socio-technical integration within city-scale adaptive systems. By synthesizing architectural paradigms, adaptation mechanisms, and emerging research directions, this review aims to identify current limitations, research gaps, and future opportunities necessary for developing resilient, scalable, and context-aware smart city ecosystems.

Case studies from cities globally show the transformational ability of adaptive multi-sensor IoT technology. Barcelona's intelligent traffic management minimizes congestion using predictive analytics, Singapore's smart energy grid balances solar, wind, and storage loads, and Amsterdam's IoT-based waste management optimizes collection [38]. These examples show concrete gains in resilience, performance, and sustainability. The readings also highlight the potential of newer technologies such as AIoT (Artificial Intelligence + IoT), blockchain-based governance, and the use of digital twins in building transparent and inclusive urban ecosystems [39]. However, the same readings identify privacy, cybersecurity, and governance as important barriers that must be tackled on an ongoing basis [40].

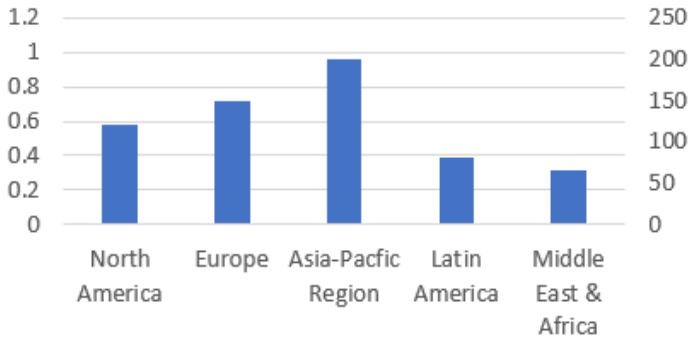


Figure 2. Global Smart City Initiatives Using IoT

Figure 2 highlights global adoption of IoT-enabled smart city initiatives, showing Asia-Pacific, Europe, and North America as leaders. The figure emphasizes adoption disparities, revealing gaps in technological readiness across regions.

In Summary, Smart cities are an innovative urban vision intended to address the challenges of rapid urbanization, sustainability, and inclusivity. IoT and flexible multi-sensor grids provide the cornerstone for the vision in linking heterogeneous data sources into reactive and predictive systems. While international programs show measurable advances, ongoing gaps in the literature document the requirements for scalable, secure, and standardized platforms. In this review, existing literature and case studies synthesize the current state of knowledge, define the opportunities and challenges ahead, and outline paths toward realizing future-ready, resilient, sustainable cities [41].

2. Method of Review

This study uses a systematic literature review to synthesize existing research on adaptive multi-sensor Internet of Things (IoT) systems for smart cities. The review process was structured to be rigorous, transparent, and reproducible. The process involved identifying relevant databases, developing search strategies, applying inclusion and exclusion criteria, and combining results from selected studies [1]. The process is described in detail below:

Using current, high-quality literature, this study relied on the world's foremost digital libraries and databases of scientific and peer-reviewed computer science, engineering, and urban studies journal articles. The following databases underwent a systematic search:

IEEE Xplore: for conference papers, periodicals, and standards on IoT, wireless sensor networks, and smart city infrastructures[2].

Elsevier (ScienceDirect, Scopus): for interdisciplinary papers on city sustainability, use of IoT, and flexible systems[3].

SpringerLink: for book chapters and articles with technology developments and conceptual uses of IoT-smart cities[4].

ACM Digital Library: database of computing-related works, covering IoT protocols, edge/fog computing, and city applications based on AI[5].

MDPI Journals (e.g., Sensors, Sustainability, Smart Cities): open-access journals that publish up-to-date results and global insights on systems of things[6].

This multi-database approach reduced publication bias and maximized coverage across technical, environmental, and governance aspects [7].

Literature searching was supplemented with a combination of pre-specified keywords and Boolean operators to ensure relevant, focused retrieval of studies. The following key search terms were used:

"smart city" AND "Internet of Things (IoT)".

"multi-sensory grid".

"IoT infrastructure" AND "urban sustainability".

"edge computing" OR "fog computing" AND "smart cities".

"adaptive IoT" AND "real-time decision-making"

Searches were performed across all fields (keyword, title, abstract, and full-text where available). Truncation and wildcard characters were used to capture keyword variations (e.g., sensor, sensing, sensors).

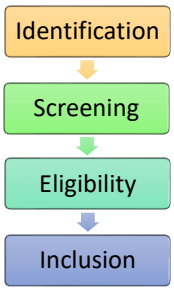


Figure 3. PRISMA-style review selection process.

The process of review can be explained with the help of Figure 3. The process of review can be explained with the help of Figure. 3. Initially,150 articles were identified across IEEE Xplore, Scopus, SpringerLink, ACM Digital Library, and MDPI databases. After duplicate removal,100 records remained. After title and abstract screening, 95 studies were retained for full-text assessment. Finally,80 articles satisfying all inclusion criteria were selected for qualitative synthesis. Duplicate and non-relevant articles at the screening level were eliminated from the pool of initially retrieved records. The dataset was further reduced through full-text review to ensure the final pool of studies directly addressed IoT-based adaptive systems and smart city infrastructure.

Inclusion and exclusion criteria were used to maintain the review's stringency.

Inclusion criteria:

Inclusion criteria for this review were structured to select high-quality, relevant research. The articles used were from 2020 to 2025, a timeframe selected to encompass the most current advances in IoT and smart city technologies [8]. The aim was to focus on peer-reviewed journals, conference papers, and book chapters to ensure academic quality and credibility. Attention was given to studies on IoT-based solutions for smart cities, multi-sensor grids, or flexible decision support systems, as these studies directly fall within the study's prime targets [9]. The literature also included studies that proposed ideas for merging IoT with city systems via frameworks, models, or architectures, as these studies provide explicit information on system design and deployment [10]. Lastly, a mix of empirical studies, case studies, and systematic reviews was included to understand both intellectual views and implementation practice within smart city development [11]. This multi-method approach allowed for a balanced and diversified synthesis of the literature.

Exclusion criteria:

To maintain the quality and direction of the review, a few exclusion criteria were used in the selection process. Non-English papers were excluded for purposes of clarity and consistency in interpretation[12]. Similarly, papers published before 2020 were excluded to focus on current developments in IoT and smart cities [13]. Papers containing merely abstracts and not providing full-text access were also excluded, as they did not contain enough detail for intensive analysis[14]. Moreover, studies beyond the scope of IoT in smart cities were also excluded to keep the review confined to its core objectives. Duplicate or identical records found through multiple databases were excluded to avoid duplication and bias. Lastly, studies without empirical support or theoretical depth were excluded to ensure the synthesis drew on only worthy and robust contributions. This screening ensured that only high-quality, contextually relevant studies were synthesized.

The review process followed the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) framework. The review process began with identification, where relevant literature was downloaded from major academic databases such as IEEE, Elsevier, Springer, ACM, and MDPI [15]. This stage relied on strategically chosen keywords to achieve comprehensive coverage of smart city literature, IoT, adaptive systems, and multi-sensory networks. After downloading the first set of records, the screening process was carried out. Duplicate entries were eliminated, and titles and abstracts were screened to exclude non-relevant studies[16]. The eligibility stage followed, in which full-text articles were carefully examined to determine whether they adhered to the previously set inclusion and exclusion criteria, as well as their relevance and quality[17]. Finally, the inclusion stage comprised a review and consolidation of the shortlisted studies that had passed all the above stages. The studies were then systematically examined and synthesized to form the basis of the review[18]. The shortlisted studies were also examined for the extraction of key aspects of data, i.e.:

Author(s) and publication year.

Objectives and scope of the study.

Emphasis on technology (communications protocols, edge computing, fog computing, AI).

Field of applications (mobility, energy, waste).

Proposed challenges that have been identified. A qualitative synthesis was then performed to integrate results into thematic categories such as infrastructure design, adaptive multi-sensor grids, privacy/security issues, and future technologies (e.g., AIoT, blockchain, digital twins) [19].

The review's methodology places special stress on a few crucial traits to increase its reliability and rigor. The first is transparency, maintained by keeping an accurate account of all stages of the process from initial database search to final synthesis of results [20]. This allows readers to follow the process and enables other users to track the same trail. The second is reproducibility, whereby other users can replicate the approach to confirm results or update the review with additional studies uncovered. To avoid leaving out significant research, the process was exhaustive, with searches conducted across databases using broad, clearly defined keywords. This minimizes bias and provides maximum coverage of available literature. Relevance was also ensured through stringent inclusion and exclusion criteria, whereby unimportant works and less influential studies were weeded out, and the remaining studies had corresponding contexts and aligned with the purposes of the study. This critical framework strengthens the study by providing a

comprehensive, evidence-based synthesis of how multi-sensor adaptive IoT systems can enable the development of smart, sustainable cities.

3. IOT Foundation and Intelligent City Infrastructure

Developing smart cities relies on deploying robust IoT infrastructures. These infrastructures act as the virtual nervous systems of cities, enabling real-time sensing, communication, computation, and decision-making. Unlike fixed, systems-based traditional cities, smart cities use dynamic IoT architectures that integrate heterogeneous sensors, smart networks, distributed computing, and secure data platforms to address complex urban issues [20]. The value of IoT infrastructure is paramount." or "IoT infrastructure is of critical importance. Without trustworthy sensing, communication, and computational foundations, the dream of a fully adaptable and sustainable smart city cannot come to fruition. A smart traffic control system, for instance, relies on vehicle sensors, high-speed networks, edge computing nodes for real-time processing, and cloud platforms for predictive insights. Energy grids also need IoT infrastructure for distributed renewable energy sources, demand prediction, and avoiding collapses [21]. The following sections discuss IoT infrastructure, including devices, communication protocols, sensor networks, computing paradigms, and adaptive decision-making. This is subsequently accompanied by an exhaustive discussion on the layer-based architecture of smart cities, with each layer perception, communication, processing, data management, applications, and security discussed extensively [22]. IoT devices provide the infrastructure foundations for a smart city. They act as the first interface between the physical and virtual worlds, extracting raw information and moving it up the stack for interpretation. They can be classified across different domains [23]:

Environmental Devices: Air quality sensors, temperature monitors, and pollution trackers provide real-time insights into environmental health. For instance, New Delhi's pollution-monitoring IoT grids enable predictive air-quality management [24]. Infrastructure Devices: Intelligent streetlights and smart meters track usage patterns and optimize resource distribution. The Barban court's smart streetlight system in Barcelona reduces energy usage by up to 30% [25]. Mobility Devices: GPS tracking-enabled buses, smart parking sensors, and traffic cameras enable predictive congestion and dynamic routing. The Singapore Connected Vehicle Grid is an example[26]. Medical Devices: Portable devices like heart rate monitors and intelligent emergency bands communicate with health systems to provide remote patient care [27]. Protocol communication is essential for interconnecting heterogeneous devices. No two protocols share the same strengths and weaknesses; each optimizes for specific applications. Table. 1 reflects their suitability, but it is essential for infrastructure design [28]: MQTT (Message Queuing Telemetry Transport): lightweight, highly efficient, and for constrained devices. Actively used for traffic control and energy metering [29]. CoAP (Constrained Application Protocol): Implements a request/response model tailored for constrained devices. In practice, it is used for environmental sensing and smart lighting [30]. HTTP: Popular but bandwidth-hungry, and best used with web services [31]. AMQP (Advanced Message Queuing Protocol): Offers reliable message transfer in enterprise applications such as financial and governmental systems [32]. LoRaWAN: Low-power, long-range, which is appropriate for long-distance infrastructure monitoring like smart meters [33]. Zigbee: The most suitable mesh network protocol for extremely dense local networks like smart homes [34].

Protocol selection influences scalability, energy efficiency, and inter-operability of smart city infrastructures [35].

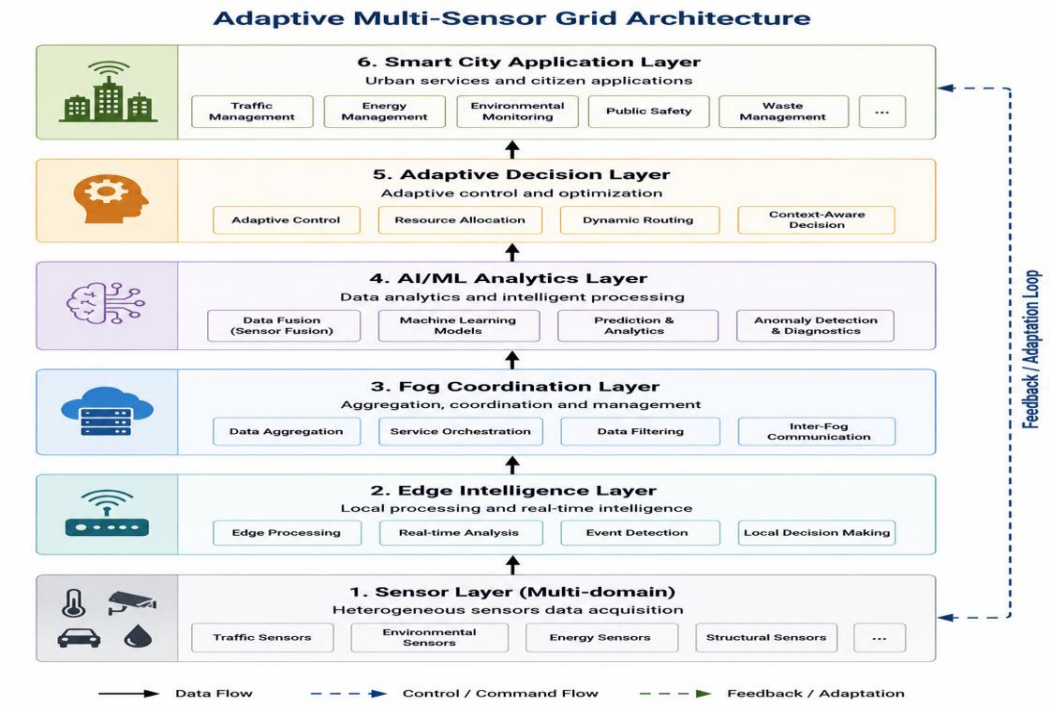


Figure 4. IOT architecture layer

Figure 4. The image illustrates a layered architecture of a smart city data ecosystem, consisting of four layers—Business, Application, Data Management, and Network. Each layer connects technologies like IoT sensors, mobile devices, data analytics, and machine learning to enable smart services such as smart transport, agriculture, and homes. Smart cities also require massive-scale sensing networks that connect numerous IoT devices. These networks also act as the central nervous system and convey environmental, infrastructure, and social-related information throughout the city. In smart city infrastructure, various network architectures are important for connectivity and efficiency [36]. Centralized networks also have wide applications in large city surveillance systems, where the huge amount of data received from sensors is routed to a centralized cloud hub for storage, processing, and decision-making purposes. While this method can support massive computation and large-scale joining, it also imposes latency and dependency on cloud availability. On the other hand, distributed mesh networks operate in a decentralized environment, where devices communicate directly with each other without relying on a central point. This topology is extremely robust and applies in smart grids and disaster scenarios, where redundancy and resilience are critical. Hybrid networks combine distributed and centralized elements. Both architectures exist within hybrid systems, combining the scalability and computing power of centralized architectures with the reliability and fault tolerance of distributed designs, and they are extremely useful for large-scale smart city applications [37]. Cloud infrastructure supports advanced storage, processing, and analytics. The advantages are scalability, compatibility with AI, and support for digital twins. However, bandwidth and latency costs can hinder real-time responsiveness [38].

The edge and fog computing lower latency by processing information closer to the source. Edge computing has proven indispensable for smart city deployments by enabling processing closer to the source, reducing latency and increasing responsiveness. In traffic control, for example, edge nodes near traffic lights can process real-time information from local cameras and sensors, identify congestion, and automatically optimize traffic-light intervals. This edge processing enables faster decision-making with minimal reliance on distant cloud servers, leading to smoother traffic and reduced waiting time. In health, wearable devices with edge processing can track vital signs continuously, such as oxygen levels, body temperature, or heart rate. Instead of streaming all raw information directly to the cloud, the wearable processes data at the edge to identify anomalies and stream immediate alerts to the user or health specialists. Only summarized or critical information is then uploaded subsequently to cloud systems for long-term storage and advanced analytics. This technique not only reduces network traffic but also increases the efficiency and reliability of health monitoring systems [39]. By harmonizing cloud and edge computing, cities gain responsiveness and long-term intelligence [40].

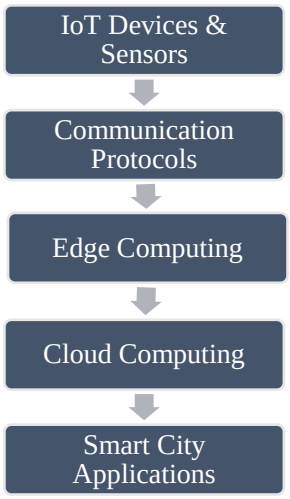


Figure 5. IoT Infrastructure Architecture

Figure 5 illustrates that IoT infrastructure is nonlinear, interconnected, and layered, with each layer depending on the integrity of the prior layer. End-to-end success for smart city applications relies on seamless connectivity from sensors → protocols → edge → cloud → applications. Adaptive decision-making distinguishes smart cities from traditional urban systems. It ensures that data is not only collected but also translated into meaningful actions. Smart city applications demonstrate how IoT and adaptive multi-sensor systems can significantly improve efficiency and responsiveness in urban services. For instance, smart lighting systems use sensors to monitor pedestrian or vehicle density, allowing streetlights to adjust brightness levels automatically. This not only enhances public safety but also reduces unnecessary energy consumption. In waste collection, sensor-equipped bins provide real-time fill-level data, enabling collection trucks to be dispatched only when needed. This approach minimizes operational costs, lowers fuel consumption, and contributes to a cleaner environment. Similarly, emergency response systems use edge-based video analysis to detect accidents or hazardous events immediately, ensuring that nearby hospitals and authorities are alerted without delay. Such rapid detection and communication can save lives and improve the overall resilience of urban safety systems. Collectively, these examples highlight how adaptive IoT-driven solutions make urban infrastructure smarter, more sustainable, and citizen-centric. This adaptability requires integrating AI algorithms, predictive analytics, and IoT data fusion into decision-making frameworks [41].

Table 1. IoT Protocols and Their Suitability

Protocol	Latency	Range	Best Use Case
MQTT	Low	Medium	Traffic monitoring
CoAP	Very Low	Short	Environmental sensing
LoRaWAN	High	Long	Waste management
ZigBee	Low	Short	Smart lighting
NB-IoT	Moderate	Long	Smart metering
5G	Ultra-Low	Wide	Autonomous vehicles

Table 1 shows that no single protocol can cover all smart city applications. Smart cities need a hybrid ecosystem of protocols, carefully chosen for specific applications, such as long-range tracking (LoRaWAN), local area mesh networks (Zigbee), or minimalist real-time communication with MQTT and CoAP. Integrating infrastructure and multi-layered design enables responsive, data-driven city systems. Theoretical implementations from Dubai, Barcelona, Singapore, and Songdo illustrate how such systems can optimize city mobility, resource use, sustainability, and citizen quality of life. But immediate challenges remain: interoperability, privacy, governance, and scalability. Resolution will demand open standards, secure protocols, inter-sector coordination, and citizen participation [50]. To manage the complexity of smart cities, IoT infrastructure is structured into six interconnected layers with distinct functions and seamless interaction [42]. Perception (Sensing) Layer – Multimodal information is provided by environment, infrastructure, mobility, and healthcare sensors. For instance, South Korea's city of Songdo utilizes building-integrated sensors for the real-time detection of energy usage [43]. Network (Communication) Layer – Transmits data using 5G, 6G, LPWAN (LoRaWAN, NB-IoT), Wi-Fi 6, Zigbee, and UAV-assisted systems. The rollout of 5G in Dubai supports autonomous vehicle deployment [44]. Edge/Fog Processing Layer – Processes local data with AI-enhanced fusion techniques. In Singapore, edge nodes process traffic congestion by adjusting traffic light intervals at interchanges on the fly [45]. Cloud and Data Management Layer – Offers centralized analytics, storage, and interoperability. Virtual twin models replicate city infrastructure, and federated learning enables privacy-preserving AI training [46].

Application Layer – Intelligent, IoT-enabled infrastructure within smart cities is designed to deliver an unprecedented set of integrated services that increase efficiency, sustainability, and citizen engagement. In smart mobility, such systems support adaptive use of traffic lanes and dynamic parking services, addressing traffic congestion, travel time, and emissions. Intelligent energy services employ real-time tracking and smart grids for demand balancing, integrating green energy sources, and reliable power distribution. In smart governance, IoT enables e-governance services and transparency platforms that increase accountability, support better decisions, and encourage active citizen participation. Finally, smart environment services use sensor networks to track pollution and optimize waste management, supporting healthier city ecosystems and sustainable natural resource use. Together, these services illustrate how multi-sensor adaptable grids transform conventional city operations into smart, responsive, and citizen-centric systems [47]. Security and Privacy Layer (Cross-Cutting) – One of the significant considerations in smart city planning is the ability to be resilient against cyber threats since IoT-equipped infrastructures process massive amounts of operational and sensitive information. One method is implementing blockchain-based authentication, securing sensors and devices' identities so it is extremely hard for rogue entities to alter or impersonate them. Moreover, federated learning offers a privacy-preserving mechanism by allowing machine learning models to be trained on distributed, decentralized data sources without exchanging raw citizen information, thereby mitigating breach risks while still enabling sophisticated analytics. In addition, intrusion detection systems keep IoT networks under constant surveillance, detecting and defeating potential cyberattacks before they become large-scale disruptions. Together, these form a multi-layer defense approach that reinforces the overall cybersecurity stance of smart cities and ensures reliability, trust, and safety for infrastructure and citizens alike [48, 49].

4. Multisensor Grid Concept

A conventional IoT sensor network generally consists of interconnected sensing devices that collect and transmit data from isolated urban environments. In contrast, an adaptive multi-sensor grid is a more advanced, intelligent architectural paradigm in which heterogeneous sensors, communication networks, edge/fog computing nodes, and AI-driven analytics operate collaboratively as an integrated urban intelligence system. The term "grid" refers not only to the physical interconnection topology of distributed sensing devices but also to a coordinated framework for data exchange, adaptive decision-making, and resource management across multiple city domains. Unlike static sensor deployments, adaptive multi-sensor grids dynamically modify sensing behavior, communication priorities, and computational workloads based on contextual conditions such as traffic density, environmental variations, energy demand, or emergency events. These systems employ distributed intelligence through edge and fog computing architectures, allowing localized processing and rapid response without relying entirely on centralized cloud infrastructure. Furthermore, sensor fusion mechanisms combine data from multiple heterogeneous sources at data, feature, and decision levels to improve situational awareness, reliability, and operational efficiency in smart city environments. A multi-sensory grid is an integrated, interconnected system that serves as the nervous system of an intelligent city. It is characterized by the large-scale deployment of heterogeneous, numerous Internet of Things (IoT) sensors that provide a unified network that captures, processes, and acts on real-time information from throughout the cityscape. The grid goes beyond single-shot data-collection systems and interlaces different sensor modalities to create a comprehensive, dynamic, and multi-faceted understanding of city operations. The overall aim is to use this combined intelligence to manage assets, services, and resources with unprecedented efficiency, and to improve sustainability and quality of life for the citizenry [51].

The strength of the multi-sensory grid lies not in individual sensors but in their interactions. By correlating information from multiple domains, the grid enables sophisticated analytics and predictive capabilities that would not be feasible with separate, siloed information. This hybrid approach underlies building smart urban solutions, from traffic control to public health tracking [52]. The multi-sensory grid's performance is characterized by the depth and width of its constituent sensor modalities. Its architecture is based on four major domains [53]. Environmental Monitoring: This layer focuses on the health of the city environment. Sensors are set up to track air quality (such as concentrations of pollutants like PM2.5 and NOx), noise, temperature, and humidity. This information serves as an essential input for formulating sustainable policies, issuing public health alerts, and identifying the environmental consequences of city activities such as traffic jams. Sharing environmental information on an IoT-based platform is a central feature of this modality [54]. Traffic and Mobility Sensing: The mobility layer is one of the best-developed domains in smart cities. This includes a vast array of sensors, including inductive loops, cameras, GPS, and radar, that can detect traffic volume, vehicle occupancy, speed, and parking space availability. Intelligent traffic control systems interpret the data and can dynamically adjust traffic light intervals, redirect cars from jammed roads, and guide drivers to available parking spaces, reducing travel time and emissions [55].

Sensing Energy (The Smart Grid): The energy grid is an infrastructure component that is tracked by its own network of dense sensors. In a smart city scenario, this "smart grid" uses sensors to track real-time electricity consumption, detect faults, and manage the injection of renewable energy sources such as solar power. This modality is important for managing grid resilience, optimizing energy distribution, and enhancing environmental sustainability through effective energy management. Latest systems incorporate AI and blockchain for distributed energy trading and management [56]. Healthcare and Public Safety Sensing: This new modality leverages sensors for a whole range of public health applications. Applications range from wearable devices for remote patient tracking, environmental sensors that can serve as inputs for epidemiological studies, and smart cameras for public safety augmentation. The goal is a responsive, proactive healthcare and emergency services infrastructure that can predict public health patterns and respond swiftly in emergencies [57]. The multi-sensory grid provides a copious and diverse amount of raw data. To derive useful information from this data, intelligent cities use advanced sensor data fusion mechanisms. Data fusion combines and integrates information and data from multiple sources to achieve greater precision,

completeness, and reliability than a single source could provide. In a multi-sensor grid, fusion enables the city to derive an overall operational scenario, identify complex patterns, and make better decisions [58].

Adaptive Mechanisms in Multi-Sensor Grids: Adaptability is a defining characteristic that differentiates adaptive multi-sensor grids from conventional wireless sensor networks and static IoT infrastructures. While traditional sensor networks primarily rely on fixed sensing schedules and predefined communication patterns, adaptive multi-sensor grids dynamically modify their sensing, computation, and communication behavior according to changing environmental, operational, and user-driven conditions. This adaptive capability enables smart city systems to respond intelligently to real-time urban dynamics while improving energy efficiency, scalability, and service reliability. One major adaptation technique is context-aware sensing, where sensor nodes adjust their sensing frequency, transmission intervals, or operational modes based on contextual information such as traffic congestion, weather conditions, pollution levels, pedestrian density, or emergencies. For example, environmental sensors may increase their sampling rates during abnormal pollution spikes while remaining in low-power mode during stable conditions. Such context-sensitive operation minimizes unnecessary data generation and conserves network resources.

Predictive activation mechanisms further enhance adaptability by using Artificial Intelligence (AI) and Machine Learning (ML) models. Instead of continuously activating all sensing devices, predictive models can forecast events such as traffic congestion, energy demand fluctuations, or abnormal environmental conditions and selectively activate only the required sensors and computational resources. This predictive strategy reduces communication overhead, lowers energy consumption, and improves operational efficiency in large-scale smart city deployments. Adaptive multi-sensor grids also employ resource-aware task allocation techniques to optimize the distribution of sensing and processing tasks across heterogeneous devices. In highly dynamic smart city environments, edge devices, gateways, fog nodes, and cloud platforms collaboratively share workloads according to resource availability, latency constraints, and network conditions. This distributed intelligence improves scalability and reduces the dependence on centralized cloud processing. Dynamic routing mechanisms are another important adaptive feature in smart city sensor grids. Unlike static routing protocols used in conventional sensor networks, adaptive routing continuously modifies communication paths based on congestion levels, link quality, node failures, and mobility conditions. Such intelligent routing improves network reliability, fault tolerance, and real-time responsiveness in urban infrastructures.

Furthermore, edge intelligence plays a crucial role in enabling rapid local decision-making within adaptive grids. By integrating edge and fog computing with AI-enabled analytics, data processing can occur closer to the source of data generation, thereby reducing latency, bandwidth consumption, and cloud dependency. Edge intelligence allows adaptive grids to support real-time applications such as traffic optimization, emergency response systems, smart energy management, and autonomous urban monitoring. Overall, adaptive mechanisms transform traditional IoT sensing infrastructures into intelligent, self-optimizing urban systems capable of learning from environmental changes and dynamically adjusting their operations to meet evolving smart city requirements. An important feature of an effective multi-sensory grid is adaptive sensing. In place of acquiring data at a fixed, predetermined rate, an adaptive system continuously changes the sensing approach in ways such as the rate at which the data is collected or which sensors are active, following real-time activity and situational inputs. This technique optimizes resource usage, such as network bandwidth and energy, while ensuring that high-quality, relevant information is obtained where it is needed most. For instance, an adaptive street lighting system activates bright lighting when pedestrians or traffic are present and dims it when none are, saving considerable energy. Correspondingly, after mobility sensors detect a traffic accident, surrounding environmental sensors might automatically increase their sampling rate to detect possible air contamination from a toxic spill [59]. Data fusion can also be categorized at different levels and involves multiple techniques, mostly driven by machine learning and artificial intelligence (AI/ML) [60].

Levels of Data Fusion:

Data-Level Fusion: This involves merging raw data streams from multiple identical sensors to derive a reading superior to any single sensor reading. For instance, averaging temperature readings from a few co-

located sensors. Feature-Level Fusion: In this approach, specific features or attributes from each sensor's information are first derived. These derived features are subsequently amalgamated. Video feed features (car shape) and radar sensor features (car speed) can be combined to obtain a more accurate vehicle classification. Decision-Level Fusion: Here, at the final stage, each sensor system gives an initial, independent decision. The separate decisions are then gathered and combined using a voting technique or probability-based approach to produce a final, robust decision. Artificial Intelligence (AI) and Machine Learning (ML): Current data fusion is driven by AI, and its ML models can discover complex correlations and patterns in distributed data that would be beyond human analyst bandwidth to find. For example, traffic management and intelligent parking systems use deep learning models to fuse camera and IoT sensor data. Probabilistic Models: Kalman filters and Bayesian inference are also widely used to handle the natural uncertainty of sensor data. They have particular success with predictive applications, for example, estimating traffic congestion or energy demand.

Low-latency fusion can be carried out close to the sensors with edge computing, which is essential for real-time applications such as automated vehicle control. Powerful cloud computing infrastructures handle computationally heavy, city-wide perspective-based large-scale fusion tasks [61]. Although adaptive multi-sensor grids offer substantial improvements over conventional IoT infrastructures, the reviewed literature reveals several unresolved architectural and operational trade-offs. Data-level fusion provides high sensing accuracy but significantly increases communication overhead and bandwidth requirements in large-scale deployments. Feature-level and decision-level fusion reduce transmission loads but may sacrifice contextual richness and introduce computational complexity at edge nodes. Similarly, while edge computing enables low-latency adaptive responses for real-time urban services, resource-constrained edge devices often face limitations related to processing capability, memory availability, and energy consumption when executing AI-driven analytics. Cloud-centric architectures provide superior scalability and computational power but introduce latency and privacy concerns for delay-sensitive applications. Furthermore, integrating heterogeneous communication protocols and sensing platforms continues to create interoperability challenges that restrict seamless city-wide coordination. These observations indicate that future adaptive multi-sensor grid architectures must balance scalability, responsiveness, computational efficiency, interoperability, and privacy preservation to support sustainable smart city ecosystems.

The Challenges of Creating a Seamless Data Fabric: Ingesting vast, diverse streams of information from a multi-sensor grid in real time is a daunting process. The success of a smart city depends on its ability to overcome crucial technical challenges related to data handling, interoperability, and network performance. It is a challenge to integrate massive, highly variable streams of data from a multi-sensor grid in real time. The sustainability of a smart city depends on its ability to solve fundamental technical issues related to data management, interoperability, and network performance [62].

Data Heterogeneity and Volumes (Big Data):

The Challenge:

The grid integrates myriad sensors that provide data in an enormous collection of types and formats (e.g., numbers, words, images, video), at varying rates, and at different quality levels. The quantity and variety of this information create a major challenge for storage, manipulation, and analysis. Smart city infrastructure must handle and process this "big data" tsunami efficiently.

The Effect:

Systems may become overwhelmed, lose detail, take longer to process, and fail to provide timely insights [63].

Lack of Interoperability and Standardization:

The Issue:

IoT devices from various manufacturers use non-standard communication protocols and data structures. This lack of standardization creates "data silos," preventing systems from communicating or exchanging information effectively.

The Effect:

This greatly restricts the multi-sensory grid's functionality by hindering full analysis that results from integrating various sources of information. The ability of systems to share and comprehend the meaning of

information through semantic interoperability is a crucial but still unaddressed concern. Evolving common system architectures would dismantle these silos [64].

Scalability:

The Problem:

The smart city isn't fixed; it's dynamic, growing, and adapting. The multi-sensory grid's infrastructure must be scalable from the ground up and support continually growing numbers of sensors and data streams without performance degradation.

The Effect:

A non-scaling system will rapidly fall out of date and need expensive overhauls. Architectures must scale and often use cloud-native design and distributed computing patterns such as edge computing [65].

Latency and Real-Time Processing:

The Problem: Critical smart city applications, such as self-driving car coordination, smart grid protection, and public safety notification systems, cannot tolerate dead time. They must transport data, run analytics, and take action within millisecond time frames (low latency).

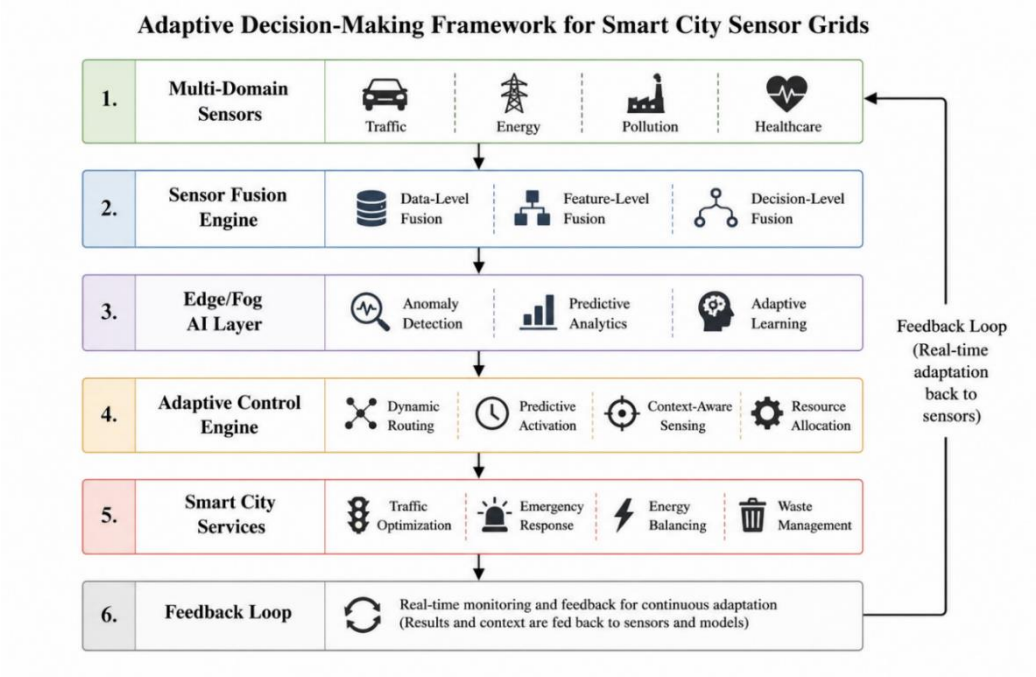


Figure 6. Framework of an adaptive multi-sensory grid for smart cities

Figure 6 illustrates the framework of a multi-sensory grid that is used for smart cities.

The Effect:

High latency can make applications inoperative or even harmful. Technologies such as 5G communication and edge computing are essential enablers, as they minimize the time it takes for the information to move from the sensor to the processing unit and from the processing unit to the sensor [66].

Data Quality, Reliability, and Trustworthiness

The Problem:

Sensor readings may be erroneous, unreliable, or incomplete due to hardware failure, improper calibration, environmental disturbances, or communication faults. Incorrect decisions based on faulty information can have severe adverse effects.

The Effect: The grid will need to incorporate robust mechanisms for validation, data cleaning, and error detection to work effectively. Data fusion can help by using redundant information to detect errors and faulty readings [67].The immense power of a real-time, integrated multi-sensory grid comes with significant risks. As the city's central nervous system, the grid is a high-value target for cyberattacks, and its data-collection

capabilities raise profound privacy concerns. Building and maintaining public trust requires that security and privacy are not afterthoughts but are foundational principles of the system's design [68].

Cybersecurity Risks:

The grid's highly interconnected nature and the often weak security of individual IoT devices create an extremely large attack surface. Attackers might cripple essential services by, for instance, controlling traffic lights, subverting the power grid, or leaking sensitive citizen information. The ethical ramifications of each such security failure on public safety are staggering [69].

Mass Surveillance and Privacy Erosion:

The same sensors that improve efficiency can also enable pervasive surveillance, tracking citizens' movements and behaviors. This raises serious ethical dilemmas about balancing urban sustainability, security, and the individual's right to privacy. Clear governance is needed to prevent misuse of this powerful technology [70]. Overcoming these problems requires advanced technology and effective policy [71].

Blockchain for Trust and Security:

Blockchain consists of a distributed, unalterable ledger that can secure communication and transactions between IoT devices. By creating an immutable event history, blockchain can increase information integrity and prevent unauthorized modifications, building a safer and more reliable system [72].

Split and Federated Learning for Privacy:

In response to concerns over centralizing potentially sensitive data for training AI models, such as for facial identification, approaches such as federated learning have emerged [73]. This enables AI models to be trained locally on edge devices without the raw data leaving its origin, thereby upholding user privacy.

Public Participation and Ethical Governance:

Technology alone cannot provide a single solution. Cities must lay out comprehensive, transparent data-governance policies that clearly outline what data is collected, for what purpose, and who can access it. Public participation in governance is also important for building trust and ensuring the smart city evolves in a way that is fair and works in everyone's interest [74].

Communication Layer: This information is interpreted and read by an AI/ML engine from the Data Processing Layer to derive insights and make future predictions. The Application Layer then utilizes this information to drive city dashboards and transmit automated control signals back to actuators, closing the adaptive feedback loop [75].

The four-tiered architecture of an adaptive multi-sensory grid for smart cities is presented in Figure 6. This encompasses the Sensory Layer, which receives raw inputs from multi-domain heterogeneous sensors and conveys them over the communication layer. The raw inputs are interpreted by an AI/ML engine within the Data Processing Layer, producing insights and predictive information. The Application Layer then consumes this information, drives it to city dashboards, and automatically pushes control signals to actuators, forming the adaptive feedback loop. However, its success would depend on overcoming the vast technical challenge of merging real-time data and, no less significantly, addressing the basic security and privacy issues at the core of such a system. The long-term goal must be to leverage this dynamic technology as much for operational efficiency as for socially inclusive development, environmental sustainability in consonance with the SDGs, and ensuring that the smart city does not widen the urban digital divide [76].

Table 2. Types of sensors in multi-sensory grid

Sensor	Parameter	Application	Accuracy
Air Quality Sensor	Carbon dioxide, Particulate matter 2.5, Nitrogen dioxide	Environmental monitoring, pollution alerts	±2% for gas concentration
Temperature &Humidity Sensor	Temperature, Relative Humidity	Climate monitoring, HVAC control	±0.5 °C, ±2% RH (Relative humidity)
Smart Meter (Energy)	Electricity consumption, load data	Smart grids, energy optimization	±1% of reading

Table 2. Types of sensors in multi-sensory grid (continue)

Sensor	Parameter	Application	Accuracy
Water Quality Sensor	pH, Turbidity, Contaminants	Drinking water safety, wastewater monitoring	±0.2 pH units, ±5% turbidity
Traffic Camera	Vehicle count, speed, congestion	Traffic flow optimization, smart mobility	90–95% detection accuracy
GPS Sensor	Location, velocity, route tracking	Navigation, fleet management, logistics	±3 meters (civilian GPS)
Waste Bin Sensor	Fill level, weight, waste type	Waste collection optimization	±5% of volume
Wearable Health Sensor	Heart rate, body temperature	Healthcare monitoring, emergency response	±2 beats per minute, ±2% SpO2(peripheral oxygen saturation)

Table 2 illustrates the wide variety of sensors used in adaptive multi-sensory grids, detailing their monitored parameters, applications, and accuracy levels. These sensors, ranging from air quality and water sensors to GPS and wearable health devices, collect real-time data that supports smart city functions such as mobility, healthcare, waste management, and environmental monitoring. Together, they form the foundation for data-driven decision-making and sustainable urban development.

5. Applications of Multisensor Grids

An integrated smart city platform is transforming urban mobility by creating a seamless, efficient, and sustainable transportation system. IoT is the foundation for such applications, enabling real-time data sensing, analytics, and evidence-based decision-making across various city domains. Applications in this segment increased tremendously from 2020 to 2025 and have focused on city resilience, sustainability, and citizen-centric services [1]. By ingesting data from various transportation and mobility streams into a centralized data platform, the system enables a wide range of cross-domain applications that redefine how goods and people move across the city [2]. The system enables an adaptive, responsive traffic control system that goes beyond fixed, pre-set timings at static traffic lights. Road sensors and GPS feed live data onto the shared platform. This provides a total city-wide view of traffic flows and congestion. This supports adaptive traffic control, where AI and multi-sensor inputs trigger IoT-based signals that dynamically change in response to real-time conditions, a technique that can reduce delays and emissions in cities like Singapore [3]. A major cause of urban congestion is the search for parking. To address this, IoT-enabled parking systems use embedded sensors to detect real-time space availability, which reduces congestion, fuel wastage, and driver frustration. Efficiency in urban parking management is further improved through AI-based allocation [4]. In the event of a breakdown or accident, the overall system can automatically call emergency services, alert digital signage, and divert other traffic to minimize secondary accidents and maintain traffic flow[5].

An integrated and harmonized public mobility infrastructure is the centerpiece of modern smart city development, aiming to break silos across different modes of transit. This development is based on the philosophy of Mobility as a Service (MaaS), in which public transportation such as bus services, rail networks, shared cycling systems, and other modes of transportation can be accessed via a single digital interface[6]. By incorporating common journey planning, the infrastructure brings together schedule and real-time location data from different transit services and enables passengers to set up the best possible routes that incorporate multiple travel modes seamlessly[7]. This not only makes travel more convenient but also promotes public and shared transportation over private cars, reducing traffic and emissions. A critical extension of this infrastructure is the inclusion of electric vehicles (EVs), where IoT sensors are used to track and manage charging infrastructure[8]. These sensors enable predictive energy allocation, optimize load balancing through

coordination with smart power grids, and ensure that power is harvested sustainably for charging EVs without stressing the grid [9].

To support mobility solutions, the energy and smart grids area also plays a critical role in powering the city sustainably and reliably. In a single data platform, energy usage patterns can be integrated with other city systems, so an intelligent grid can handle renewables, minimize energy wastage, and remain resilient to perturbations [10]. Together, these systems form an ecosystem in which transportation and energy infrastructures work in concert to advance sustainability, efficiency, and quality of life for city inhabitants [11]. A smart grid modernizes conventional power infrastructure by accommodating two-way communication between utilities and consumers, making it an intelligent network that increases efficiency, control, and sustainability [12]. One of its primary functions is incorporating IoT-based smart grids, where smart meters and networked devices gather real-time information to balance energy supply and demand effectively [13]. This infrastructure enables easy integration of renewable energy sources like solar panels and windmills so that green energy can be efficiently distributed across the grid without compromising stability [14]. Smart street lighting is another critical use case, using adaptive IoT-based systems that can automatically dim or brighten based on vehicle presence or pedestrian activity [15]. Furthermore, predictive maintenance makes energy systems' reliability and resilience even stronger. By analyzing data recorded by sensors on the network's transformers, power cables, and other infrastructure, AI applications can identify early signs of wear and tear, faults, or eventual collapses [16]. This predictive approach enables timely maintenance and intervention, reducing the frequency and duration of power outages and lowering repair costs. Together, these applications indicate that smart networks supported by IoT and advanced analytics form the foundation for sustainable, efficient, and future-proofed city energy systems [17].

The conceived framework is central to directing cities toward a sustainable and resilient energy mix, ensuring city development remains consistent with environmental and resource protection objectives [18]. One core component of this framework is managing renewable energy integration, where generation information from wind and solar sources is coupled with weather forecasts and current consumption patterns [19]. This allows grid managers to accurately forecast fluctuations in generation-based energy and adjust supply accordingly, keeping the system stable and optimizing green-energy use [20]. To further improve reliability, the framework uses IoT-supplemented microgrids that act as semi-autonomous energy systems and can identify faults and restructure in real time [21]. The microgrids add fundamental resilience by ensuring power availability during blackouts, natural disasters, or grid failures, thereby protecting vital services [22]. Another key area is supporting electric vehicle charging infrastructure, where the framework offsets the increased energy demand from electric vehicles within total grid capacity [23]. Through predictive analytics and incentive mechanisms, it promotes off-peak charging, avoiding system overloads and optimizing efficiency[24]. Beyond energy, the system spans the broader arenas of environmental sustainability and resource efficiency, using interrelated data streams to reduce the city's ecological impact [25]. Through measures such as waste reduction, resource conservation, and support for a circular economy, the system ensures that city operations not only use the latest technologies but also operate in an environmentally conscious manner [26].

Table 3. Applications of multi-sensory grid

Domain	Sensor Type	IoT Role	Benefits
Smart traffic management & mobility	Multi-sensor systems including cameras, infrared sensors, and GPS in vehicles	IoT connects vehicles, sensors, and traffic signals into a cohesive network. It enables real-time monitoring and data collection to manage urban transport systems.	This leads to optimized traffic flow, reduced congestion, and improved urban mobility. It can also include advanced adaptive street lighting to save energy.

Table 3. Applications of multi-sensory grid (continue)

Domain	Sensor Type	IoT Role	Benefits
Smart parking	Ultrasonic or magnetic sensors in parking spaces	The IoT framework connects parking sensors to provide real-time data on parking availability.	This revolutionizes urban mobility by guiding drivers to available spots, saving time and fuel. It is a key component of an intelligent city's transportation infrastructure.
Smart energy grids	Smart meters and sensors integrated into the grid	IoT facilitates intelligent energy management across grids, often using AI and blockchain. It allows for the monitoring of smart home energy systems, including renewable energy sources and electric vehicles.	Benefits include enhanced environmental sustainability, increased energy efficiency, more resilient power grids, and decentralized energy trading.
Smart waste management	Ultrasonic sensors to detect fill levels in bins	IoT-enabled environments use multi-agent simulations to compare and optimize waste management models.	This optimizes waste collection routes, saving fuel and reducing operational costs.
Environmental monitoring	Air quality, temperature, and humidity sensors	IoT provides a platform for collecting and sharing environmental data across the city from various sensors.	Facilitates better urban planning and policy-making based on real-time environmental data, contributing to a more sustainable and healthier city.
Smart healthcare	Wearable devices, remote monitoring equipment	IoT connects various technologies to innovate healthcare delivery in smart cities.	Improves the accessibility and efficiency of healthcare services for residents in developing nations.

Table 3 highlights key smart city domains such as traffic management, parking, energy, waste, environment, and healthcare along with the sensor types, IoT roles, and benefits associated with each. It demonstrates how IoT-enabled sensor networks enhance efficiency, sustainability, and quality of life by enabling real-time monitoring, optimized resource use, and improved urban services**.** This proactive CCTV tracking boosts security, prevents incidents, and builds citywide robustness [44]. Environmental monitoring for smart cities uses IoT-enhanced infrastructure to generate real-time insights that support sustainability and public health [27]. Networks of air quality stations with IoT sensors track harmful gases such as CO_2, NO_2, and PM2.5, and this information contributes to health programs and city-level policymaking [28]. The systems can also provide real-time warnings when smoke and other pollutants exceed safe levels, allowing authorities to take special measures and protect at-risk communities [29]. In addition to air quality, IoT is also important for noise and carbon footprint tracking [30]. Sensors in densely populated or densely trafficked locations measure noise pollution, guiding city planning and quality-of-life improvements [31]. Sensor information also comes together in carbon dashboards to track emissions, enabling cities to monitor performance against sustainability targets and climate actions [32]. At the same time, this use enables cities to take anticipatory action on environmental issues and support healthier, more sustainably livable cities [33]. In contemporary smart cities, AI and IoT technologies are being integrated to enhance waste and water management systems, making them more efficient and sustainable[34]. Intelligent waste collection relies on bins with fill-level sensors that provide real-time information, enabling collection services to use predictive routing for trucks[35]. This minimizes unnecessary travel, reduces fuel consumption, saves on operational expenses, and reduces environmental degradation.

To supplement this, automated waste segregation uses AI-based robotic systems that separate recyclable contents from mixed waste streams [36]. These greatly minimize the amount of waste that ends up in landfills but encourage circular economy practices by reusing valuable materials. In water management, similar devices with IoT continuously monitor leaks, assess water quality, and track distribution efficiency [37]. This supports the preservation of water sources, reduces losses, and ensures safe distribution, leading to long-term urban sustainability [38]. IOT technologies are having a transformative impact on healthcare and public safety in smart cities[39]. Wearable devices with integrated IOT sensors enable tracking of patient vital signs over a prolonged period, such as heart rate, oxygen levels, and body temperature[40]. These devices enable real-time transfer of information to healthcare professionals, which facilitates early detection of deviations, timely corrections, and enhanced long-term patient tracking[40]. In hospitals, IoT systems streamline operations through improved patient flow, optimized inventory tracking, and enhanced coordination of emergency responses [41]. Public safety, beyond healthcare, also benefits substantially from IoT-based CCTV systems with integrated AI analytics [42]. These systems track city spaces in real time to identify deviations from normalcy or suspicious activity and alert authorities promptly [43].

In smart cities, IoT-based platforms greatly enhance participatory governance by giving citizens real-time access to city data[45]. Real-time traffic flow, air and water quality, and energy consumption dashboards allow residents to engage directly with city operations and foster shared responsibility and inclusivity in decision-making[46]. This transparency not only strengthens civic engagement but also ensures that policies are conceptualized with high public input[47]. In addition, blockchain-based governance platforms enhance transparency and accountability by creating tamper-proof records of data transactions[48]. These networks safeguard the integrity of city information, reduce the chances of manipulation, and build increased trust between the government and citizens[49]. Together with blockchain and IoT technologies, they form a governance system that is transparent, accountable, participatory, and aligned with the citizen-centered smart city vision [50].

6. AI/ML Integration

The integration of Artificial Intelligence (AI), particularly Machine Learning (ML) and Deep Learning (DL), transforms static, sensor-based smart cities into dynamic and truly intelligent systems [30]. While the Internet of Things (IoT) provides the city's sensory nervous system by collecting massive streams of real-time data, it is AI that acts as the brain, making sense of this information so that dynamic decisions can be taken, predictive insights can be obtained, and constant optimization of city services can take place [31]. This convergence, also known as the Artificial Intelligence of Things (AIoT), allows urban infrastructure not only to react quickly to immediate conditions but also to learn, adapt, and predict future requirements [32]. The goal is a responsive city fabric that increases efficiency, sustainability, and quality of life by embedding intelligence at the operational core of the city [33]. Machine Learning and Deep Learning models form the core of making adaptive decisions in smart cities [34]. They allow systems to discern patterns from data, predict outcomes, and make complex decisions programmatically without explicit human coding [35]. In a city environment, this means city services can dynamically adapt to the shifting needs of the citizen base and the environment [36]. For example, a smart traffic control system can use ML models on real-time traffic data streams from IoT sensors to programmatically tune traffic light timings to reduce congestion [37].

This shifts from hard-coded, time-based static signals to a dynamic, adaptable system that can intelligently react to real-time conditions [38]. Deep learning, a more advanced subset of ML, uses complex neural networks to discern subtle patterns in large datasets and is especially suitable for highly complex city problems [39]. A refined ensemble deep learning model, for example, can be used to develop smart parking systems that direct drivers to available spots, reducing traffic and pollution [40]. Likewise, multi-agent reinforcement learning systems may optimize recommendations for charging electric vehicles and, through experience and error, determine the optimal approach for balancing grid load and driver convenience [41]. This adaptability and learning ability are vital for long-term city administration [42]. In the long run, as cities grow and need to respond to new demands, AI-enabled systems can grow with the city [43].

The unification of neuro-symbolic AI, which brings together the strengths of symbolic reasoning and neural networks, offers the promise of a new-generation platform for city intelligence that can handle increasingly complex and nuanced decision-making scenarios [44]. Ultimately, the goal of both ML and DL is to move beyond limited automation and create systems that possess genuine adaptivity, steadily improving performance and efficiency over time [45].

ML Paradigms for Adaptive Multi-Sensor Grids:

Different Machine Learning (ML) paradigms suit different adaptive smart city tasks, depending on sensor data characteristics, computational constraints, and operational requirements. Supervised learning approaches are widely used in applications where labeled historical data is available, such as traffic flow prediction, energy demand forecasting, pollution estimation, and infrastructure fault detection. Algorithms such as Support Vector Machines (SVM), Random Forests, and Deep Neural Networks (DNNs) can achieve high prediction accuracy in structured urban environments. However, supervised models require large annotated datasets and frequent retraining to remain effective in dynamic city conditions. Unsupervised learning techniques are particularly useful for anomaly detection, clustering, and pattern discovery in large-scale sensor networks where labeled data may be unavailable or incomplete. These models can identify abnormal traffic behavior, unusual energy consumption, cyberattacks, or environmental irregularities without predefined training labels. Nevertheless, unsupervised approaches may suffer from reduced interpretability and sensitivity to noisy sensor data.

Reinforcement Learning (RL) has emerged as a promising paradigm for adaptive decision-making and autonomous optimization in smart city environments. RL models continuously learn optimal actions through interactions with dynamic urban systems and are well suited to adaptive traffic signal control, autonomous energy balancing, smart parking optimization, and resource-aware network management. Multi-agent reinforcement learning systems are particularly beneficial in distributed sensor grid architectures where multiple agents cooperate to optimize city-wide operations. However, RL models often require extensive training time, high computational resources, and stable simulation environments. Despite their advantages, deploying ML models within adaptive sensor grids introduces several practical challenges. Resource-constrained edge devices often have limited processing power, memory, and energy, making it difficult to deploy large AI models. Techniques such as model compression, pruning, quantization, and lightweight neural architectures are therefore essential for enabling efficient edge intelligence. Furthermore, adaptive smart city environments continuously evolve, causing concept drift in sensor data distributions. Consequently, AI systems must support online learning and continuous model adaptation to maintain long-term prediction accuracy and operational reliability.

The working deployment of AI in smart cities happens via a few basic abilities, namely predictive analytics, anomaly detection, and optimization [46]. These capabilities allow city managers to act proactively rather than reactively, resolving issues in advance and allocating resources as optimally as possible [47]. Predictive analytics leverages historical and real-time data to forecast future trends and events [48]. By analyzing data from IoT platforms, cities can optimize urban infrastructure and resource management [49]. This could involve predicting energy demand to prevent blackouts in a smart grid, forecasting traffic congestion to reroute vehicles in advance, or anticipating infrastructure maintenance needs before a failure occurs [50]. Anomaly detection is an important function for securing and making smart city infrastructure highly resilient[51]. In a city with thousands of web-connected devices, the risks of a cyberattack loom large [52]. AI models, especially those using federated and split learning technologies, can monitor network traffic within an IoT network and identify unfamiliar patterns that may indicate a cyberattack, enabling swift action and threat mitigation [53].

Optimization is perhaps the most widespread application of AI in making cities smarter [54]. AI algorithms are used to find the best possible solution to complex problems with multiple variables [55]. This includes optimizing waste management models through multi-agent simulations to determine the most efficient collection routes [56], enhancing urban sustainability through AI-driven energy efficiency strategies [57], and optimizing the performance and cost of big data processing with regional computing [58]. From street lighting systems that adapt to real-time conditions to the complex management of power grids, optimization ensures

that urban services are delivered with maximum efficiency and minimal waste [59]. The real strength of a smart city that can adapt lies in the seamless, hybrid combination of AI and IoT [60]. This mutually dependent relationship, where IoT sensors produce a continual flow of information, and AI programs take that information and make it into smart action, is the bedrock of the current smart city scenario. This combined model, referred to as AIoT, is transforming how cities are run and experienced. Hybrid systems appear in many smart city applications. In smart mobility, the combination of IoT, multi-sensor data fusion, and AI is central to conceptualizing smart traffic monitoring systems for roads. IoT devices on the roads and on vehicles gather information, which AI interprets for traffic control, accident detection, and real-time feedback for drivers. Smart energy systems also use a hybrid of 6G IoT, AI, and even blockchain to design sustainable and robust energy systems.

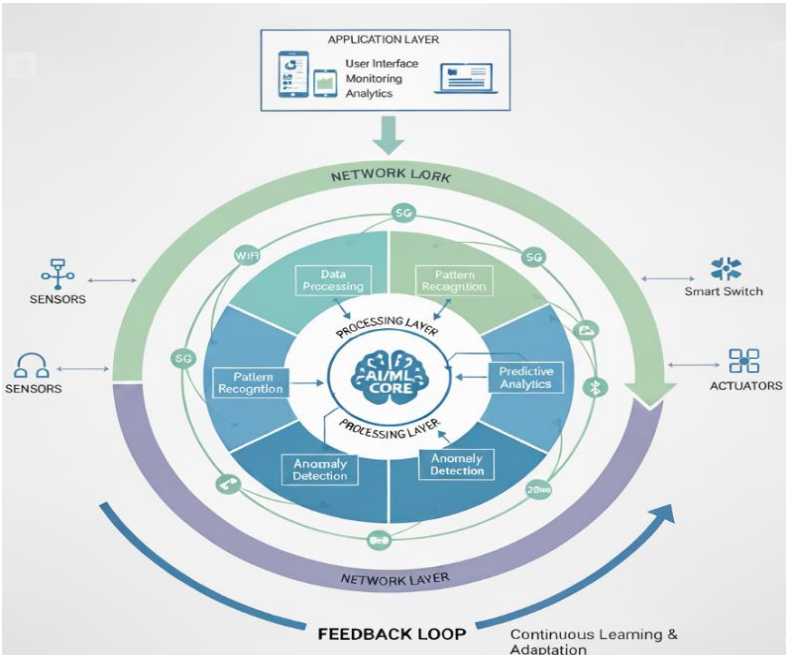


Figure 7. AI-enabled adaptive IoT framework

Figure 7 illustrates an AI-enabled adaptive IoT framework through a circular flow. It shows data moving from Sensors (Perception Layer) through a Network Layer to a central Processing Layer where an AI/ML Core performs data analysis, pattern recognition, and anomaly detection. The AI then sends decisions back through the Network Layer to Actuators, completing a Feedback Loop that enables continuous learning and adaptation, all managed and monitored through an Application Layer.

7. Challenges and Constraints

Establishing smart cities, although promising, faces numerous challenges that hinder success and proper execution. Challenges range across technological, financial, and ethical areas, all of which require careful attention and planning to overcome [61]. These include the system's ability to scale and integrate properly, safeguard large quantities of sensitive data while addressing privacy and ethical concerns, and manage the high costs and hardware constraints of installing sophisticated technologies in cities [62]. One of the main issues in developing smart cities is making deployed systems both scalable and interoperable [63]. Scalability involves a system's capacity to handle increasing workloads or expand to support growth. With increasing urban populations, smart-city infrastructure must support an ever-increasing number of devices and data volumes without performance degradation [64]. The large number of sensors and IoT devices needed for an extensive smart city network provides an incredible volume of data for processing, storage, and management [65]. Interoperability, the capacity of diverse systems and devices to communicate and share data without hindrances, is also an issue[66]. Intelligent cities may also depend on an assortment of technologies supplied by different makers, some of which may employ different standards and protocols. The absence of

standardization creates "information silos," where data from one system (say, traffic management) may not integrate straightforwardly with another (say, public safety), hindering the promise of holistic urban management[67]. To work effectively as an integrated whole, the disparate components of a smart city — from traffic sensors and smart grids to public safety networks—must also be able to communicate coherently. Making this possible requires defining common standards and open platforms that enable seamless integration among diverse technologies and functions [68].

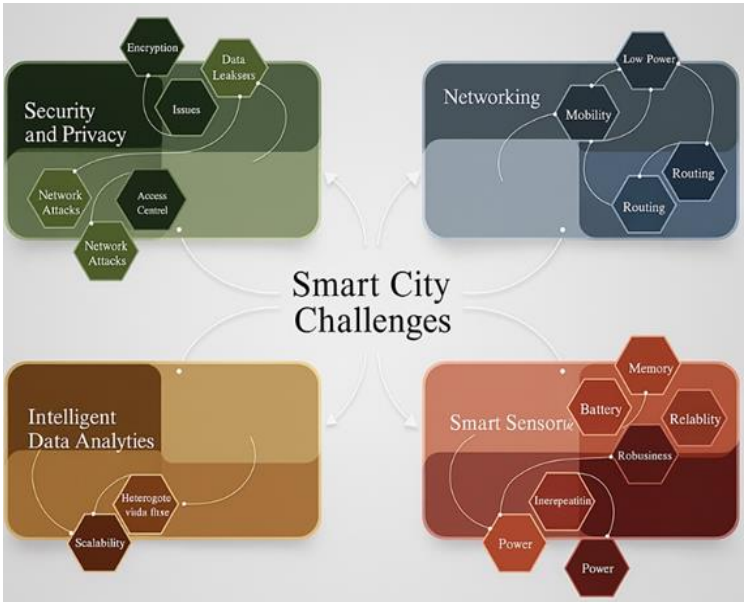


Figure 8. Challenges in Smart City

Figure 8 presents the key challenges in smart city development, categorized into four areas: Security and Privacy, Networking, Intelligent Data Analytics, and Smart Sensors. Each category highlights specific issues such as data leaks, network attacks, scalability, interoperability, power, and reliability, reflecting the complex technological and infrastructural hurdles in building smart urban environments. The wide collection of data inherent in the smart city raises deep security, privacy, and ethical issues [69]. Because IoT devices are highly interconnected, the attack surface for the entire smart city infrastructure is large, making it susceptible to cyberattacks. Adversaries may compromise critical urban infrastructure such as traffic management, power supply, or emergency response, thereby threatening public safety [70]. Guaranteeing the security of the interconnected infrastructure presents an ongoing challenge. Emerging technologies such as blockchain are being researched to develop more secure and transparent data management frameworks for smart cities[71]. Beyond security, ongoing data collection on citizens' movement, behavior, and activities also poses serious privacy issues. Data can be abused for surveillance or commercial exploitation by corporations or government entities without citizens' approval. This creates an important ethical tightrope: balancing the use of data for the common good with safeguarding individual privacy. Smart city development must therefore be guided by strong ethical considerations and sound data protection laws to build trust among people and ensure the technologies work for all people[72]. An ethical issue also arises: the potential for an "urban digital divide," where unequal access to technology may increase underlying social inequalities. Hardware limitations and high implementation costs also hinder implementation of smart city projects. Infrastructure installation required, i.e., sensors, communication infrastructure (e.g., 5G), data centers, as well as smart devices, is very costly. High capital expenditures might prove the biggest challenge for small cities or new economies with limited finances. For example, establishing an IoT sensor network for traffic and environmental monitoring for smart grid management requires enormous capital expenditure. Apart from the financial implications, there are also physical and hardware constraints. Most IoT devices also impose constraints on power consumption, data processing, and data storage. Installing sensors in the remote or hard-to-access parts of the city may also pose logistics challenges. Additionally, the fast-evolving nature of technology means hardware may become outdated quickly, requiring ongoing maintenance spending and infrastructure upgrades to keep

it running. Long-term fiscal sustainability also raises concerns, as cities need to establish sustainable business cases that cover both the start-up costs of deployment and the recurring costs of operation.

Open Research Challenges and Future Gaps

Despite substantial progress in adaptive smart city infrastructures, several unresolved research challenges continue to limit the large-scale deployment and operational efficiency of adaptive multi-sensor grids. One major open issue involves interoperability among heterogeneous IoT devices, communication protocols, and sensing platforms. Although multiple standardization efforts have been proposed, seamless integration across large-scale urban infrastructures remains difficult because of differences in data formats, communication standards, and vendor-specific architectures. Scalability also remains a critical concern in adaptive smart city environments. As sensor density and the volume of real-time urban data increase, centralized cloud-based systems often struggle to provide low-latency processing and efficient resource allocation. While edge and fog computing architectures reduce communication delays, optimal workload distribution between edge, fog, and cloud layers remains an open research problem. Artificial Intelligence (AI)-driven adaptation mechanisms introduce additional technical complexities. Although Machine Learning (ML) and Deep Learning (DL) models improve predictive analytics and automated decision-making, deploying such models on resource-constrained edge devices requires lightweight architectures, model compression, and energy-efficient inference mechanisms. Furthermore, AI models operating in highly dynamic urban environments must continuously address challenges related to concept drift, real-time adaptation, and changing environmental conditions.

Privacy-preserving techniques such as federated learning have emerged as promising solutions for decentralized AI training in smart city systems. However, federated learning performance in highly heterogeneous and non-independent and identically distributed (non-IID) sensor environments remains an unresolved challenge. Variations in sensor quality, communication latency, device capability, and local data distributions may negatively affect model convergence, stability, and prediction accuracy. Similarly, blockchain-based frameworks improve transparency and trust in distributed smart city infrastructures but introduce computational overhead, latency, and scalability limitations. Traditional blockchain architectures are often unsuitable for high-frequency real-time sensor data streams because of transaction throughput constraints and energy consumption requirements. Beyond technical limitations, socio-technical concerns such as unequal sensor deployment, digital inequality, mass surveillance risks, and ethical governance remain insufficiently explored in the literature. Future research must therefore focus not only on technological optimization but also on fairness, transparency, sustainability, and citizen-centric governance models for adaptive multi-sensor smart city ecosystems.

Table 4. Challenges vs solutions for adaptive multi-sensory grids

Challenge	Solution
Big data management	Regional computing can optimize the performance and cost of managing large volumes of data. Edge computing can also be utilized. Real-time data analytics helps in optimizing urban infrastructure and resource management.
Cybersecurity and privacy	A privacy-preserving and secure framework can be developed using blockchain and machine learning. Hybrid quantum architecture offers another solution for smart city security. Federated and split learning can enable anomaly detection of IoT cyberattacks. Blockchain and federated learning can be combined for enhanced cybersecurity in scalable smart city frameworks. Ethical dilemmas between sustainability and privacy require balancing and mitigation strategies.

Table 4. Challenges vs solutions for adaptive multi-sensory grids (continue)

Challenge	Solution
Interoperability	Smart cities need clear interoperability requirements. Semantic interoperability is a key research area that enables different systems to communicate effectively.
Scalability	Scalable smart city frameworks can be designed using technologies like blockchain and federated learning. For large-scale AIoT systems, multi-level split federated learning is a potential solution.
Energy consumption & sustainability	AI-driven energy efficiency strategies can enhance urban sustainability. Smart grids with sensors contribute to environmental sustainability. This includes intelligent energy management using 6G IoT, AI, and blockchain, as well as decentralized energy trading on blockchains.
Network connectivity	5G and LPWAN-IoT technologies can be used to improve connectivity for smart cities and remote areas.
Multi-sensor data fusion	Data fusion approaches are essential for IoT-based smart cities. Multi-sensor information fusion allows combining data from various IoT-enabled sources.
The digital divide	Smart city development should focus on being a social transition towards inclusive development to counter the urban digital divide.

Table 4 outlines major challenges in smart city development—including big data management, cybersecurity, interoperability, scalability, sustainability, and the digital divide—and pairs them with innovative IoT-driven solutions. It highlights how technologies such as edge computing, blockchain, AI, federated learning, and 5G can overcome these barriers to build resilient, secure, and inclusive smart cities.

8. Future Directions

The development of the smart city will see revolutionary breakthroughs through the interplay of different underlying technologies [60]. The long-term evolution is towards a highly integrated, smart, safe, and responsive city[61]. This will be achieved through next-generation wireless networks such as 5G and 6G, the decentralization of artificial intelligence via Edge AI and federated learning, the use of blockchain for increased security and transparency, and digital twin applications for high-end real-time simulation and governance of a city [62]. The convergence of 5G and future 6G networks will be a foundation for the next-generation smart city [63]. Next-generation wireless technologies will aim to transcend limitations of current networks by providing ultra-high bandwidth, ultra-low latency, and the ability to support a vast quantity of concurrent IoT devices [64]. 5G will act as the basis for communication infrastructure, which will support real-time communication of data for a plethora of applications such as smart traffic systems, automatic vehicles, and virtual public services [65]. The evolution of 5G and LPWAN-IoT architectures will be indispensable for optimizing smart city applications, primarily in rural locations[66]. As cities evolve and become increasingly data-intensive, seamless and expedient communication supported by 5G and 6G will be indispensable for managing the vast amount of information from an infinite number of sensors and connected objects [67]. This increased interconnectivity will enable increasingly complex and responsive cities, with systems ranging from dynamic energy grids that can intelligently manage power distribution to interlinked public safety networks that can respond quickly in emergencies [68]. The interface between these future networks and the IoT will facilitate an interconnected urban fabric, enabling cities that are leaner, greener, and more liveable [69].

To handle huge volumes of data from urban IoT networks, there is a distinct shift toward distributed data processing with Edge AI and federated learning [70]. Rather than pushing all data to a centralized cloud for processing, edge computing processes data in city, closer to the point of origin. This significantly reduces

latency, which is essential for real-time applications such as vehicle autonomy and citywide smart traffic management. This also reduces the expenses associated with pushing and storing vast volumes of data in the cloud. Federated learning also augments this setup [71]. This enables AI models to be trained from different data sources (e.g., different sensors or entities) without raw data ever leaving its point of origin. This approach is especially useful for smart-city applications, where data privacy and security concerns prevail. For example, one can apply federated learning to identify cyberattacks on IoT networks or improve traffic flow across the city by learning from distributed sources of information while keeping individual data points private [71]. Together, Edge AI and federated learning enable a decentralized, responsive, effective, and privacy-preserving architecture for urban intelligence that lets cities learn and adapt in a distributed fashion [71]. Blockchains are also an increasingly significant catalyst for addressing the security, privacy, and transparency concerns at the core of smart city infrastructures. In supply chain transactions and other interactions across various IoT devices and systems, blockchain can facilitate secure, transparent transactions and data management through a decentralized, immutable ledger. This is valuable for applications involving sensitive information or multi-party interactions, such as multi-party energy trading for smart energy grids, secure public governance, and multi-party supply chain transactions. In smart grid applications, blockchain can facilitate transparent and secure peer-to-peer energy transactions between consumers and support a decentralized, efficient energy platform [72]. In public governance, blockchain can facilitate tamper-proof records and enhanced public engagement and confidence. Further, when combined with machine learning and IoT, blockchain can provide a privacy-preserving, secure platform for smart city operations and protect against unauthorized use and manipulation of information. Integrating blockchain represents a significant step toward developing robust, trustworthy digital infrastructure so the information underlying smart city services remains reliable and secure [72].

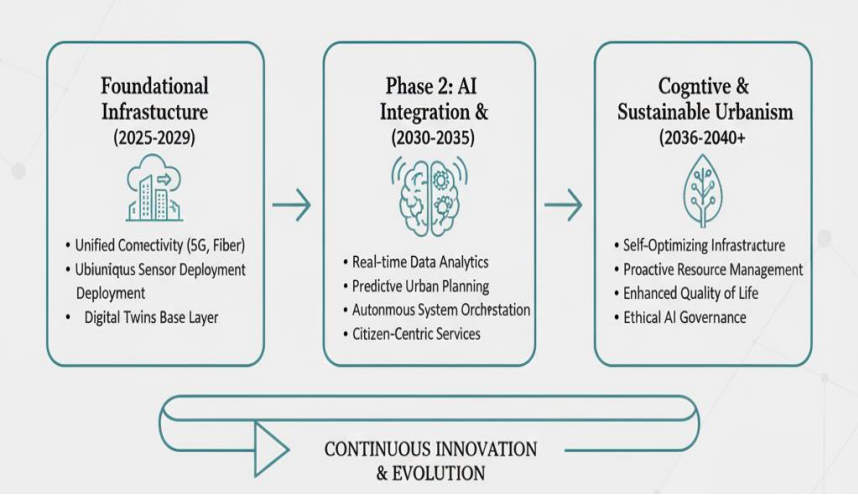


Figure 9. Future roadmap for adaptive multi-sensory smart cities.

Figure 9 outlines a three-phase roadmap for developing adaptive multi-sensory smart cities. It begins with Foundational Infrastructure, progresses to AI Integration & Adaptation for advanced data analytics and urban planning, and culminates in Cognitive & Sustainable Urbanism focusing on self-optimizing infrastructure and ethical AI governance, all driven by continuous innovation.

City planning and administration have a landmark innovation in the form of digital twin technologies [73]. A digital twin is a current, real-time replica of a city, including its structures, infrastructure, and operational systems [74]. The model is continuously updated with inputs from IoT sensors and enables city planners and managers to monitor city dynamics, simulate the impact of hypothetical changes, and optimize city operations virtually before changes take place in the physical world [75]. For instance, traffic flows can be simulated with a digital twin and tested for the impact of new traffic signal timings or layouts to alleviate congestion [76]. The environmental effects of new-building projects can also be simulated, waste collection routes optimized, or emergency response protocols planned for different scenarios [77]. A comprehensive

study of 4,200 papers highlights the growing importance and volume of studies on this topic through a thorough bibliometric analysis [78]. By providing a dynamic, citywide perspective, digital twins support better-informed, data-based decision-making [79]. This technology is central to the notion of urban intelligence, with powerful capabilities for designing greener, resilient, and effective cities [80].

9. Conclusions

Smart city development is propelled primarily by the Internet of Things (IoT), which can be described as the nervous system of cities. Multi-sensor grids enabled by IoT form the basis of modern urban ecosystems through the dynamic accumulation of transportation, energy, waste, and environment-related data. This constant flow of information informs urban intelligence and enables city managers to optimize public services, alleviate traffic congestion, optimize energy use, and improve residents' overall quality of life. When paired with Artificial Intelligence (AI), big data analytics, and other new digital technologies, IoT enables cities not just as networked infrastructures but as intelligent, responsive, and sustainable ecosystems. Despite rapid development, numerous problems remain unaddressed. One of the foremost is interoperability: the lack of global standards frequently hampers seamless communication between platforms and, as a result, creates disjointed "data silos." No less problematic is scalability, as fast-expanding populations and surging numbers of IoT devices create tremendous data flows that strain existing infrastructure. Cybersecurity is also another central issue. As city systems grow increasingly interconnected, they increasingly risk falling prey to cyberattacks that can harm critical services such as traffic control, public health, or electrical distribution. Though promising technologies such as blockchain, federated learning, and hybrid quantum architectures have been proposed as protections, further study is needed to develop scalable, robust security solutions. Financial sustainability is another vital barrier. Installing and operating the needed hardware—such as sensor networks, 5G and 6G connectivity, data centers, and advanced IoT-enabled devices — requires massive capital investments. Many cities, especially in developing nations, lack funds for such infrastructure, which is why innovative new models and funding mechanisms must be introduced that are both feasible and sustainable. One of the differentiating factors of successful smart cities is the merging of AI, particularly Machine Learning (ML) and Deep Learning (DL). While the sensory layer of the city consists of IoT, its cognitive layer consists of AI that interprets, analyses, and translates this data to enable predictive insights, adaptive decision-making, and dynamic system optimization. This amalgamation, sometimes described as the "Artificial Intelligence of Things (AIoT)," turns static infrastructures into dynamic systems that can respond quickly to current issues as they happen and predict future needs. ML and DL allow systems to learn from fluctuating urban data, automate sophisticated decision-making, and optimize service provision. For instance, AI-based traffic control systems can use real-time data to dynamically optimize signal patterns, minimizing congestion and emissions compared with fixed, pre-programmed systems. Similarly, deep models can identify complex patterns in urban datasets, supporting applications such as predictive maintenance, optimized parking allocation, and efficient energy distribution. Reinforcement learning mechanisms also extend flexibility by repeatedly optimizing strategies through trial and error and are particularly useful for applications such as electric vehicle charging infrastructure management. The evolution toward neuro-symbolic AI promises even more by combining data-driven learning with rational capabilities so that cities can address increasingly complex and nuanced issues. This way, AI does not merely automate routine tasks but creates genuinely adaptive systems that evolve with time and shifting city needs. The revolutionary role of AI in smart cities is most evident in three core functions: predictive analytics, anomaly detection, and optimization. Predictive analytics supports proactive administration by forecasting infrastructure needs, traffic patterns, and energy demand. Anomaly detection improves robustness by spotting abnormalities in IoT network traffic that might indicate cyber threats and enables immediate response. Optimization optimizes resource use across functional domains such as waste management, energy networks, and transportation infrastructure, eliminating waste and maximizing efficiency.

Hybrid AI-IoT solutions are breaking barriers of innovation with tightly coupled sensing technologies and smart analytics. In transportation, multi-sensor-based IoT with AI is used for real-time tracking and dynamic traffic control. In energy, smart grids with AI, blockchain, and advanced connectivity (5G/6G) enable

optimal integration of renewables, load balancing, and decentralized trading. Future paradigms like federated learning enhance privacy and scalability by training AI models in a distributed way without centralizing sensitive information. These hybrid systems represent a significant milestone toward increasingly automated and highly cognitive systems, making cities smart but also resilient, sustainable, and highly responsive to the needs of the populations they serve. The future smart city vision involves closing the distance between technological possibilities and socio-economic imperatives. Meeting interoperability standards, ensuring effective data protection, and creating sustainable financial models are critical prerequisites. Similarly, cities also need to put inclusivity first, so that city development and technological advances can be shared across communities and not used to exacerbate inequality. Looking ahead, new technologies such as digital twins for real-time simulation, 6G-based ubiquitous connectivity, and new-generation AI architectures will play a determining role in achieving the next generation of city intelligence. Overcoming current technical, ethical, and financial barriers will unlock the transformative value of smart cities, making them not only technology-intensive but also socially just and environmentally sustainable. Despite significant advancements in IoT-enabled smart city systems, the transition from conventional sensor networks to adaptive multi-sensor grid architectures remains an evolving research challenge. This review highlights that future smart cities will increasingly depend on distributed intelligence, adaptive sensing, AI-driven decision-making, and real-time sensor fusion for achieving resilient and scalable urban management. However, several unresolved issues persist, including interoperability among heterogeneous infrastructures, deployment of lightweight AI models on resource-constrained edge devices, privacy-preserving learning over non-IID sensor data, and low-latency coordination across large-scale urban environments. Emerging technologies such as 6G-enabled ultra-reliable low-latency communication (URLLC), federated learning, digital twins, and edge AI are expected to address many of these limitations by enabling real-time adaptation, predictive urban analytics, and decentralized intelligent control. Future research should therefore focus on developing self-optimizing, context-aware, secure, and socially inclusive adaptive multi-sensor grid frameworks that support sustainable and equitable smart city development.

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