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Internet of Things for Urban Infrastructure: Applications, Challenges, and Future Directions – A Review

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ABSTRACT

The Internet of Things (IoT) has emerged as a transformative technology in the development of urban infrastructure, enabling real-time data collection, intelligent decision-making, and integrated service delivery. This study explores the implementation of IoT in various urban domains, including transportation management, environmental monitoring, smart parking, structural health surveillance, and smart city integration. The findings highlight significant improvements in operational efficiency, system resilience, and environmental sustainability. However, large-scale adoption still encounters challenges such as cybersecurity risks, interoperability issues, device reliability, and maintenance demands, along with socio-economic barriers including high implementation costs, limited technical expertise, and complex regulatory frameworks. To address these challenges, the study recommends adopting advanced technologies such as edge computing, artificial intelligence, and blockchain, establishing global interoperability standards, and fostering cross-sector collaborations. Furthermore, innovative financing models and inclusive public policies are essential to ensure secure, efficient, and sustainable IoT deployment. The research contributes to a deeper understanding of the role of IoT in shaping future smart cities, providing a framework for policymakers, urban planners, and technology developers.

1. INTRODUCTION

Convergence of digital technology and urban infrastructure has also become a milestone in modern city construction since it is being driven by the exponential growth of Internet of Things (IoT) technologies and applications into the core urban infrastructure networks [1]. Since its establishment in the late twentieth century, IoT has evolved from the conceptual model of networked devices to a mature technological complex that reconfigures the operation of urban infrastructure and its governance [2][3]. The period of the 2020s to 2025 has witnessed gigantic technological developments like sensor technology, communication protocols, edge computing power, and artificial intelligence integration. The scale of IoT devices has grown exponentially and is estimated at as many as 50 billion connected IoT devices as of the year 2022, which creates networks of intelligent devices, sensors, and systems that track things in real-time, gather data, and take decisions autonomously [4][5]. Such technological foundation has revolutionized traditional infrastructure management practice in the form of converting static, reactive systems into proactive, dynamic networks that can sense ahead of time, optimize the utilization of resources, and respond intelligently to changing conditions in top areas such as water management, transportation systems, power distribution, waste management, and structural monitoring [6][7][8].

The relevance of IoT in today's urban infrastructure management manifests itself in three key axes: operational efficiency, system resilience, and environmental sustainability. IoT solutions have been impressive in improving infrastructure operating efficiency, with smart water management solutions delivering water resource savings of up to 30% and reducing operational expenditure, and IoT-driven energy management solutions reporting gains of between 24% and 28% in energy consumption [7][9]. Predictive maintenance via IoT sensors has reduced downtime and maintenance costs significantly while ensuring uninterrupted service delivery through sophisticated anomaly detection and demand forecasting. Besides enhancing efficiency, IoT technologies have a highly critical role to play in infrastructure resilience through the provision of early warning systems, automated fault detection, and adaptive response mechanisms that enable end-to-end monitoring of infrastructure wellness and environmental conditions [10]. The environmental sustainability benefits are equally staggering, as smart city deployments using IoT technologies realize tremendous carbon emissions reductions, such as reported up to 28% yearly carbon footprint and 27.5% reduction in daily water consumption through real-time optimization and smart resource management [5][11].

This literature review to present a comprehensive analysis of IoT uptake in city infrastructure, examining the existing level of uptake in various infrastructural areas, the key benefits and issues, evaluating current technology patterns, and providing strategic recommendations for optimum IoT implementation frameworks. The criticism addresses the most important knowledge gaps like the integration of sustainability metrics with measurement of IoT performance, large-scale urban deployment scalability issues, and the need for holistic frameworks to support technological capabilities with limited practical implementation possibilities. Research methodology encompasses a systematic search through literature for the five-year time frame of 2020-2025 through numerous academic databases like IEEE Xplore, Scopus, Web of Science, and ScienceDirect by carrying out well-designed keyword combinations concerning IoT, infrastructure in cities, smart cities, and infrastructure management. The integration high-quality publications employs quantitative and qualitative approaches to identify performance measures, technological developments, and future challenges, targeting studies that have measured benefits, challenges of implementation, and scalability effects to provide evidence-based results for scholars, policymakers, and practitioners in this rapidly expanding field of IoT-based city infrastructure.

1.1 Contributions of This Review

This review brings forth a number of new insights into the current state of knowledge about Internet of Things (IoT)-based urban infrastructure. In the first place, unlike most existing review papers which focus majorly on applications within single domains such as transportation systems, energy management, or environmental monitoring, this paper presents a multidomain review of IoT applications in multiple critical domains of urban infrastructure such as transportation systems, environmental monitoring, smart parking systems, structural health monitoring, and last but not least, smart city platform integration. By taking a holistic approach, this paper allows for a more integrated interpretation of the role played by multiple IoT applications in influencing urban infrastructure systems as a whole. In the second place, unlike most current reviews which focus majorly on technological architecture levels such as devices, networks, edge cloud computing, and applications, this paper takes into consideration the convergence level between technological architecture considerations such as security, networking, economic viability, government regulatory issues, and social infrastructure readiness. As such, this paper goes beyond current reviews which focus majorly on technological considerations alone, presenting evidence into the systemic nature of IoT adoption in urban infrastructure systems. Through this integrated architectural framework, this paper allows the reader the benefit of evaluating current IoT applications and their subsequent potential applications and impact levels at which urban infrastructure systems can be made more efficient, more resilient, and more sustainable. Finally, this paper identifies current priority research and development trends and their corresponding applications within urban infrastructure systems from a strategic planning point of view by taking into consideration emerging trends such as edge intelligence, federated learning, and last but not least, IoT-interoperability.

2. IOT: CONCEPT AND ARCHITECTURE

Internet of Things (IoT) is one of the models of advanced technology that has evolved significantly from the initial idea to the current concept in contemporary texts as an advanced system of connecting devices, sensors, and systems to enable increased functionality in many areas of human endeavor [12][13]. In modern academic vocabulary, IoT is a very technology-oriented setting wherein numerous intelligent devices and intelligent interface-enabled devices are interconnected to deliver integrated services in daily life from smart homes and e-businesses to healthcare centers and smart infrastructure management [14][15]. The unstated assumption that underlies IoT is the reification of ordinary items and infrastructural pieces from static, lifeless equipment to intelligent, networked equipment that can sense, communicate, compute, and might actuate, with predictions that everything will be Internet-enabled by 2025 and more than 50 billion Internet-enabled IoT devices predicted. Current literature describes IoT as innovation and edge-cutting field bringing new technological concepts with a complete set of promising advantages, essentially offering smart and communicating nodes integrated into changing global pattern infrastructures that are capable of predicting demands, optimizing resource utilization, and responding to changed conditions wisely [16][17].

The basic building components of IoT structure include four primitive building blocks supplemented to each other to provide cross-infrastructure functionality [18]. Sensors form the cornerstone of construction, the first connection of physical to digital space through conversion of environmental change to quantities, measurement of physical quantities, and conversion of analogue signals to streams of digital information, with more recent use taking advantage of an assortment of sensor devices including accelerometers, humidity detectors, movement sensors, and thermal detectors, and achieving up to 99.92% level of accuracy in medicine and industry [19]. The connectivity feature entails a range of networking technologies and communication protocols from the short-range technologies such as Wi-Fi, BLE, and Industrial IoT protocols to the long-range cellular networks and LoRaWAN technologies supporting unobtrusive exchange of data among IoT devices, edge systems, and cloud platforms

[20][21][22]. Cloud platforms form the third building block, providing elastic computing capacity, data storage and analytics capabilities necessary to handle high volumes of IoT data, ingest different forms of data and enable real-time analysis. The analytics module also includes sophisticated data fusion, processing, and analysis methods that transform raw sensor data and convert it into intelligent insights for infrastructure management by using artificial intelligence, machine learning, blockchain, and federated learning principles to facilitate predictive maintenance, anomaly detection, demand forecasting, and optimization algorithms [23][24][25].

Table 1. IoT Architecture Layers

Layer Name	Components	Functions
Physical/Device Layer	Sensors, Actuators, RFID Tags, Embedded Systems	Data collection, enviromental sensing, physical interaction
Connectivity Layer	Wi-Fi, LoRa, 5G, Bluetooth, Zogbee	Data transmission, network communication, protocol conversion
Edge Computing Layer	Edge Servers, Gateways, Local Processing	Real-time analytics, latency reduction, local decision-making
Cloud Computing Layer	Data Storage, Big Data Analytics, Machine Learning	Scalable computing, advanced analytics, data management
Application Layer	User Interface, Dashboards, Mobile Apps	Service delivery, visualization, decision support systems

The infrastructure in Table 1 pattern based on IoT typically follows a layering pattern with deliberate aggregation of features and elements into different layers, the most common of which is the five-layer pattern through the physical layer, connectivity layer, edge computing layer, cloud computing layer, and application layer. Physical layer is comprised of embedded devices, sensors, and actuators interacting directly with physical infrastructure elements, collecting actual data on environmental parameters, structure condition, and operating parameters, while connectivity layer provides connectivity through supported network protocols and enables end-to-end data transport over heterogeneous IoT networks [26][27]. Edge computing layer is subsequently the core architectural component for processing and handling data at the local site, avoiding latency and bandwidth requirements and enabling real-time decision-making for time-constrained infrastructure applications, running sophisticated algorithms like fuzzy logic controllers, machine learning algorithms, and optimization algorithms [28]. Cloud layer infrastructure is designed to provide end-to-end data processing, storage, and analytics capability to facilitate large-scale infrastructure management on colossal scales with multiple clouds aggregated to facilitate scale-up deployment, while the application layer serves as the user interface and service delivery module converting processed IoT data into actionable intelligence, visualization dashboards, and automation control capability [29][30].

3. APPLICATIONS OF IOT IN INFRASTRUCTURE

3.1 Transportation and Traffic Management

Real-time traffic control is the most significant application of IoT technology to the urban transportation system, utilizing advanced sensor networks, wireless communications systems, and advanced analysis to provide end-to-end visibility of traffic flows throughout the urban network [31][32][33]. Advanced deployments utilize technologies such as wireless sensor networks (WSNs), computer vision-based vehicle detection, and in-road embedded sensors to provide real-time traffic flow, congestion rate, and vehicle motion pattern monitoring through machine learning-based systems such as SENets-based models with 94.5% accuracy for detecting traffic anomalies and 30% signal control optimization over traditional practices [34]. They demonstrate significant operating benefits including 25% lower congestion levels and 12.7% better air quality through the use of smart traffic control methods [35], and with the addition of innovative anomaly detection features based on multi-dimensional Singular Spectrum Analysis (mSSA) methods for identifying suspicious vehicle activity and impending accidents. Intelligent tolling systems have now been implemented to displace traditional toll plaza management with Radio Frequency Identification (RFID) and Automatic Number Plate Recognition (ANPR) technologies, with RFID systems providing 98% at speeds under 80 km/h and 95.5% accuracy of the classification of vehicles by type [36], and ANPR systems on the YOLOv8 architecture offering 99% accuracy of recognition of characters on number plates with vehicle detection and approximately 73% accuracy for environmental factors [37]. Emergency vehicle routing systems utilize such IoT technologies in a bid to provide next-generation priority systems based on LoRa technology, GPS tracking, and traffic light control that self-adapts to dynamically optimize routes and reduce ambulance travel time by smart coordination of emergency services and traffic management systems [38][39][40].

Table 2. RFID vs ANPR Technologies Comparasion

Characteristics	RFID Technology	ANPR Technology
Technology Type	Radio Frequency	Computer vision
Detection Accuracy	98% <80km/h	95% overall
Speed Limitations	Speed sensitve	Speed independent
Cost	Moderate cost	Higher cost
Infrastructure Requirements	Readers and tags	Camera and proc
Security Features	Encrypted	Plate encrypt
Applications	Toll and access	Multi-purpose

Despite the potential offered by IoT-based transport networks in Table 2 to revolutionize, certain inherent issues within the area of cybersecurity and integration with installed bases serve as disincentives to mass adoption and operational robustness. Higher use of networked transport infrastructure exposes more attack surfaces to Advanced Persistent Threats (APT) and distributed denial-of-service attacks, whereas heterogeneity of device ecosystem and resource constraints of embedded systems form impediments to the enforcement of suitable security policies. 95-98% APT detection is achieved through benchmark sets with federated deep neural network-based threat detection systems that are privacy-preserving, but cybersecurity threats are still encountered to protect sensitive location information, driving behavior, and individual mobility patterns collected through such systems [41]. Legacy system integration is also more intricate in the case that existing transport infrastructure is leaning towards use of proprietary protocols, legacy communications protocol, and inflexible architectures unsuitable for existing available IoT technology, so special consideration to interoperability, security issues, and continuity of services has to be made in integrating with already deployed Supervisory Control and Data Acquisition (SCADA) systems and transport infrastructure [42][43][44]. The integration of IoT technologies into current transport infrastructure means scalability, interoperability, and long-term sustainable maintenance, which must be well planned and deliberated in order to effectively utilize the potential of intelligent transport technology as well as satisfy future security and privacy needs [45][46].

Although existing studies demonstrate that IoT-enabled transportation systems significantly improve traffic flow efficiency, congestion management, and real-time decision-making, the reviewed literature largely adopts domain-specific and isolated system designs. Most implementations focus on sensor accuracy and algorithmic performance without sufficiently addressing interoperability with other urban infrastructure systems. Moreover, scalability and long-term operational costs remain underexplored, particularly in large metropolitan environments. These limitations indicate a need for integrated, cross-domain transportation solutions aligned with broader smart city platforms.

3.2 Environmental Monitoring

IoT-based environment monitoring systems have now become indispensable components of infrastructure in the maintenance of public health and urban sustainability, and air quality monitoring equipment has been shown to be highly effective in the monitoring of major pollutants like fine particulate matter (PM2.5 and PM10), nitrogen dioxide (NO_2), sulfur dioxide (SO_2), carbon monoxide (CO), and ozone (O_3) in urban cities [47][48][49]. Urban-scale management, the sensors record wide-area monitoring coverage, recording very high PM2.5 concentrations of 85.7 ± 8.6 µg/m³ to 222 ± 22 µg/m³. CO_2 readings record between 555.6 ± 1.0 ppm and 560.8 ± 1.0 ppm, while Air Quality Index (AQI) rates calculate from 171.3 for cleaner places up to 444.2 for dirty urban hotspots, enabling real-time public health notifications and environmental decision-making [50]. Water monitoring networks complement air quality programs with large sets of sensors including pH measurement, dissolved oxygen (DO), temperature, total dissolved solids (TDS), turbidity, and many pollutants, more sophisticated implementations including 98.2% implementation rates of sensor-based pH monitoring using SEN0169 and HI-98107 sensors, 92.9% implementation rates of temperature monitoring using DS18B20 sensors, and 62.5% implementation rates of dissolved oxygen monitoring using SEN0237 and MAX30102 sensors [51]. Machine learning-based water quality systems are incredible with prediction capability wherein AdaBoost regressor models achieve a minimum of 14.37 counts/100 mL mean absolute error (MAE) in prediction of E. coli, and LSTM neural network models achieve 0.00074 Mean Squared Error (MSE) and 0.98 R-squared values in prediction of nitrate concentration [52][53].

Table 3. IoT Sensor Performance & Challenges

Parameter Type	Sensor Examples	Accuracy Range	Deployment Cost	Maintenance Issues
Air Quality (PM2.5, NO2, CO)	SDS011, MQ-7, MQ-135	85-95% (calibr.)	Low ($25-100)	Drift component, environment exposure
Water Quality (pH)	SEN0169, HI-98107, pH-4502C	98.2% coverage	Medium ($50-200)	Regular calibr., probe clean

Water Quality (DO)	SEN0237, MAX30102, OxyGuard	92.9% implement	High ($100-500)	Membrane replace, drift corr.
Temperature/Humidity	DS18820, DHT22, SHT30	95-99%	Low ($5-50)	Low maintenancem environment protection
Particulate Matter	PMS5003, SPS30	75-90% vs ref	Medium ($30-150)	Fan clean, calibr. drift

Despite significant technological advancements in Table 3, IoT environmental monitoring systems have enormous issues of sensor accuracy, maintenance requirements, and deployment costs that impact system scalability and reliability [54]. Sensor accuracy problems are most problematic in low-cost IoT rollout, where the 8.5% error rate of uncalibrated environmental sensors versus 4.3% for well-calibrated systems, and the need to re-run calibration requirements on a regular schedule due to concept drift and wear and tear in the environment, are non-viable operational costs that limit high-scale deployment [55]. Deep reinforcement learning-based high-accuracy calibration models have solution possibilities of 96.17% accuracy for various sensor faults like bias, drift, total failure, and accuracy loss, whereas low-cost CO sensor calibration methods with one-dimensional convolutional neural networks have a significant amount of accuracy improvement [56]. Maintenance problems encompass weather exposure sensor deterioration, power management of wireless sensor networks, and the logistics problem of servicing thousands of scattered sensors across city blocks, whereas economic problems include the initial deployment high cost, ongoing operational expenses, and prolonged maintenance requirements impinging on system economic viability [57][58]. Global multi-unit calibration approaches have the potential to achieve significantly lower costs in terms of universal calibration standards for sets of sensor units of a particular type, and self-supervised learning-based approaches have the potential to decrease needs for labeled calibration data and allow more liberal sensor calibration procedures [59][60].

The literature on IoT-based environmental monitoring consistently highlights improvements in data granularity, real-time pollution tracking, and early warning capabilities. However, many studies emphasize technical feasibility over governance and data integration challenges, resulting in fragmented monitoring systems. Scalability and sustainability emerge as dominant concerns, especially for continuous long-term deployments. Future research should therefore move beyond pilot-scale implementations toward standardized and interoperable architectures that support policy-oriented environmental management within smart city ecosystems

3.3 Smart Parking Management

Multi-sensor-based parking detection is an innovative method of controlling parking in cities using diverse sensing technologies for providing all-around and homogeneous sensing of cars in different environments and conditions [61][62]. Smart parking systems based on modern IoT offer varied sensor modalities like ultrasonic sensors to sense distance, magnetic sensors to detect metal cars, infrared sensors to sense motion, and computer vision systems using deep YOLO models for precise vehicle detection. Multi-sensor fusion methods have been shown by studies to significantly enhance the detection rates, with ultrasonic sensors achieving 97% slot occupancy, magnetic field sensing achieving 98.81% using PNI PlacePod sensors, and extremely achieving 99.68% balanced accuracy with computer vision-based YOLO models that used hand-crafted datasets of over 3,400 images of parking [63]. Proactive deployment employs LoRaWAN data transport protocols of low-power, long-range for communicating to support widespread deployment in big urban parking lots with ensured reliability of connectivity and real-time status reporting. Such systems are reported to have high working advantages such as 40% parking search time reduction, real-time notification with less than 1-second delay, and mobile app interaction without interruption, giving drivers real-time parking availability information [64][65].

Table 4. Smart Parking Detection System

Sensor Type	Detection Tech	Accuracy	Advantages	Limitations
Ultrasonic	Distance (HC-SR04)	97% slot	Weather resist	Limited Range
Magnetic	Magnetic Field	98.81%	Long battery	Adjacent cars
Infrared	Motion/Hear PIR	89%	Low Power	Weather affect
Computer Vision	Image YOLO	99.68%	High precision	High computer
LoRa/IoT	Wireless Multi	95-99%	Long range	Network depend

In table 4, integration of machine learning algorithms with IoT parking data offers sophisticated demand forecast capability with immense data monetization and revenue optimization value in smart city scenarios [66]. Better accuracy prediction models incorporating Random Forest, Extra Tree, and LightGBM algorithms demonstrate better performance in parking availability prediction where the LightGBM model achieves $R^2 = 0.9742$ and RMSE = 0.1580 for time series prediction and Random Forest algorithms achieve higher efficiency when dealing with large data, long-term parking space availability prediction. These forecasting abilities enable dynamic pricing strategies maximizing parking authority revenue and maximizing drivers'

availability for stalls while game-theory-based solutions yield Nash equilibrium prices maximizing revenue to parking management at minimal cost to drivers [67], [68], [69]. Data monetization includes opportunities beyond traditional parking fees to premium insights for city infrastructure planning, traffic flows, cutting-edge EV charging, and business opportunities, with parking usage data and duration insights generating streams of revenue for such businesses as car service, retail analytics, and city mobility companies. Smart parking has data-driven business models with subscription schemes, micropayments, and data-sharing modalities of public-private partnerships, and there is vehicle identification and plate reading in real time at up to 30 frames per second enabling commercially scaleable applications at 98.0% accuracy and 99.6% precision by advanced edge computing deployments [70][71][72].
Existing smart parking solutions predominantly focus on localized efficiency gains, such as reducing search time and traffic congestion. While these systems demonstrate measurable operational benefits, they often rely on standalone platforms with limited data sharing capabilities. The matrix synthesis in Figure 2 indicates moderate emphasis on interoperability and governance challenges, suggesting that current implementations rarely integrate parking data into broader urban mobility strategies. This highlights the need for scalable and interoperable parking systems that function as components of integrated urban transportation frameworks.

3.4 Structural Health Monitoring

Smart bridges with IoT sensor networks is a revolutionary approach to infrastructure maintenance that includes integrated multi-parametric sensing systems that enable continuous tracking of the most important structural parameters like vibration, strain, deflection, temperature, and seismicity. Contemporary SHM installations with IoT are utilizing diverse sensor technologies like QMEMS accelerometers with ultra-low self-noise density of 20 ng/√Hz for earthquake early warning, piezoelectric sensors with precise bolt tension monitoring with battery life up to 5+ years and LoRa range extension of 3.8 km, and MEMS sensors for indirect prediction of bridge deflection using edge AI capabilities [73] [74][75]. Wireless sensor networks with high-performance exhibit excellent performance, and LoRa LPWAN-based systems are proved to be exemplary in terms of data rate, precision, and affordability for bridge soundness monitoring on a continuous basis. Real-world demonstrations by actual systems, including successful field trials for the Chijing bridge in Shanghai and the Yeonggwang Bridge test bed, validate the effectiveness of IoT-supporting SHM systems in providing automated real-time notifications regarding structural damage along with economical and scalable monitoring methodologies. These systems include high-end edge computing capabilities that enable local processing and real-time alert generation, with dual-core STM32H7 microcontrollers enabling real-time earthquake early warning (EEW) systems as well as automated threshold-based alarms via SMS, email, and mobile apps [76][77].

Table 5. IoT Sensors for Smart Bridge SHM

Sensor Type	Measured Parameter	Detection Capability	Accuracy/Perf	Applications
QMEMS Accelerometes	Vibration, Seismic Activity, Structural Response	Real-time earthquake detection, structural vibration analysis	20 ng/√Hz self-noise, high sensitivity	Earthquake early warning (EEW), SHM system
Piezoelectric Sensors	Guided waves, Bolt tension, Crack detection	Preceise pre-tension force tracking, crack identification	Robust and scalable tracking	Bolted joint monitoring, damage detection
Strain Gauges	Structural deformation, Load Monitoring, Stress analysis	High-precision stress and load measurement	High accuracy measurement	Load distribution analysis, structural integrity
MEMS Sensors	Deflection, Inclination, Displlacement	Bridge deflection behavior prediction	Cost-effective, edge AI capabilities	Indirect SHM, drive-by monitoring
Wireless Vibration Sensors	Dynamic response, Modal analysis, Structural changes	Low-power continuous monitoring, modal identification	5+ years battery life, 3.8km range	Contiuous health monitoring, remote sensing

In Table 5, the integration of reinforcement learning algorithms and IoT sensor data enables high-end optimization of early damage detection functionality, outperforming the traditional shortcomings of manual inspection methods using smart, adaptive monitoring solutions. Reinforcement learning-based structural health monitoring uses Markov decision processes for the optimal planning of inspection intervals and maintenance, with feedforward artificial neural networks adapted for adaptive control of time-unknown and changing-over-time structural systems serving as effective damage detection for impulse and white noise external excitation conditions [78], [79]. High-end deep reinforcement learning (DRL) environments that incorporate Partially Observable Markov Decision Processes (POMDP) achieve remarkable performance improvements, for example, autonomous robotic inspection systems with 57% better crack detection rates than conventional raster scanning methods and reducing the entire inspection time by 50%. Machine learning enhanced damage detection systems incorporating support vector machines (SVM), k-nearest neighbor (KNN) algorithms, and ensemble learning methods record maximum accuracy levels, with auto-damage detection systems achieving an accuracy level of 97.59% in structural damage categorization and Gene Expression Programming (GEP) models that predict damaged surface areas and load-carrying capacity with accuracy levels of 99% and 97% respectively. The novelty-detection paradigm facilitated by reinforcement learning algorithms produces reliable indicators of damage by comparing expected and received system performance, allowing for the early application of intervention strategies that are highly cost-efficient in contrast to conventional maintenance while avoiding catastrophic failure of the structure through proactive monitoring and smart decision-making capabilities [80][81].

IoT-based structural health monitoring has been widely adopted for critical infrastructure assessment due to its high accuracy and predictive maintenance capabilities. Nevertheless, the literature reveals a strong dependence on high-cost sensing technologies and specialized expertise, raising concerns regarding scalability and economic feasibility. Cybersecurity and data governance challenges are particularly pronounced in SHM applications, given the sensitivity of infrastructure data. These findings suggest that future SHM research should prioritize cost-efficient sensing, secure data architectures, and integration with city-level asset management systems.

3.5 Smart City Integration

IoT platform interoperability is a central challenge and enabler for successful smart city implementations, requiring sophisticated integration solutions addressing heterogeneity at device, protocol, and data format levels among different stakeholder realms. Present-day smart cities are complex distributed systems consisting of multiple stakeholders that make use of different sensor platforms, communication protocols, and data storage mechanisms posing huge interoperability challenges without integration plans [82][83]. Advanced interoperability solutions utilize standard interfaces such as the OGC Sensor Observation Service and the OGC SensorThings API, enabling end-to-end data transfer between disparate IoT platforms through lightweight web services encoding observations "on-the-fly" conforming to international standards. The semantic web technologies play an important role in achieving the cross-domain interoperability, with ontology-based frameworks capable of enabling efficient information exchange among heterogeneous IoT platforms while addressing the problem of incomplete data formats, alternative semantic approaches, and varied data structures [84][85]. Existing distributed architectures employ multi-layered models comprising Data Monitoring Layer (DML), Data Storage Layer (DSL), Data Enhancement Layer (DEnL), and Data Exchange Layer (DEL) which show astounding performance gains like up to 41.23% boost in throughput and 29.19% decrease in latency compared to centralized designs, apart from offering mass deployment support with hundreds of sensor nodes and providing cross-platform compatibility [86].

Table 6. Smart City IoT Platform Interoperability Case Studies

City/Location	IoT Application Domain	Platform Integration Technology	Performance Metrics	Key Benefits
Barcelona & Santander, Spain	Smart Parking	Semantic interoperability via Global IoT Services	Multi-platform data exchange	Reduce vendor lock-in and unified mobility services
Métropole de Lyon, France	Heat Wave Mitigation	Open IoT ecosystem with Horizon 2020	Enhanced interoperability between components	Imporved emergency response and reduce regulatory
IIIT Hyderabad, India	Multi-domain monitoring	Distributed architecture with 4 layers	41.23% throughput improvement 29.19% latency reduction	Scalable cross-platform compatibility
Queen Elizabeth Olympic Park, London	Environmental monitoring	InterSensor Service with OGC APIs	Unified data visualization	Standardized cross-platform data integration
Pune, India	Air Quality Monitoring	Bayesian optimization ML models	R^2 values of 0.9742 RMSE of 0.1580	Predictive analytics for pollution contro

In Table 6, real-world implementations demonstrate the disruptive potential of interoperable IoT platforms through multiple case studies in environmental monitoring, emergency response, and urban mobility applications. The Métropole de Lyon heat wave prevention project is a best-practice implementation of IoT ecosystem deployment by using EU Horizon 2020 framework technologies that significantly increase interoperability between system components and reduce regulatory barriers for collaborative service co-creation practices. Barcelona and Santander's smart parking scheme illustrates semantic interoperability through Global IoT Services (GIoTS) to enable data consumption continuity from five heterogeneous smart city IoT deployments to provide integral parking guidance and mobility suggestions while eliminating vendor lock-ins [87][88]. Environmental monitoring application scenarios demonstrate excellent performance outcomes, with Pune's air quality monitoring networks recording R^2 values of 0.9742 and RMSE of 0.1580 utilizing Bayesian optimization techniques to tune hyperparameters for ensemble regression model hyperparameter tuning. Advanced integration techniques combining Complex Event Processing (CEP) with SPARQL queries enable real-time decision-making by stakeholders, rule-based pattern matching over air quality data streams received from sources in Central Pollution Control Board and processed with Apache Kafka to enable better urban environmental management. The MARGOT distributed edge computing system exhibits effective IoT resource discovery in smart cities with lower discovery latency and bandwidth consumption and enabling domain-aware and secure access to IoT resources in regular usage and emergency response situations [89][90].

Studies on smart city platforms emphasize the potential of centralized data integration and real-time urban management through IoT technologies. Despite these advantages, the reviewed literature indicates persistent challenges related to interoperability, governance, and institutional coordination. Many platforms remain technologically advanced yet operationally fragmented due to regulatory and organizational barriers. This underscores the importance of holistic platform design that aligns technological capabilities with governance structures and policy objectives.

3.6 Conceptual Framework of IoT-Based Urban Infrastructure

On the basis of a synthesis of an existing body of literature, this research work aims to conceptual and contextualize the role of Internet of Things (IoT) technology in the development of urban infrastructure. The proposed conceptual framework takes into consideration four intersecting layers, which, in sum, address the complexity of IoT deployment for a smart city infrastructure. The first layer conceptualizes the infrastructure domain of the IoT, which is categorized into transportation infrastructure, environmental intelligence, parking management, structural health management, and a comprehensive intelligent city platform. The infrastructure domains address the fundamental application domain of IoT, which has significant usage for the aforementioned infrastructure applications and is identified by an analysis of the relevant existing bodies of literature. The second layer conceptualizes the architecture of IoT, which is identified by sensing & actuation, communication, edge & cloud computing infrastructure, and application services. The architecture identifies the fundamental usage of IoT, which addresses heterogeneous devices and processes, real-time sensing, and decision support systems for different applications of urban infrastructure. The third layer is conceptual and identifies challenges for IoT deployment for all infrastructure applications. The layer addresses a host of challenges, which include risks of security and privacy, limitations of interoperations, scalability and cost, and governance and human readiness, which are identified by analysis of fundamental applications of IoT and address impediments of IoT deployment for a comprehensive infrastructure, which is fundamental for a sustainable and reliable infrastructure for a smart city. The fourth layer conceptualizes the benefits of IoT deployment, such as efficiency of infrastructure, infrastructure robustness, and sustainable infrastructure, which addresses fundamental urban applications, including support for evidence-based decision support of urban infrastructure and urban policy.

To clarify the conceptual structure and analytical synthesis of the reviewed literature, this study presents two complementary visualizations. Figure 1 illustrates the overarching conceptual framework of IoT-based urban infrastructure, while Table 7 provides a matrix-based synthesis mapping key challenges across major urban infrastructure domains.

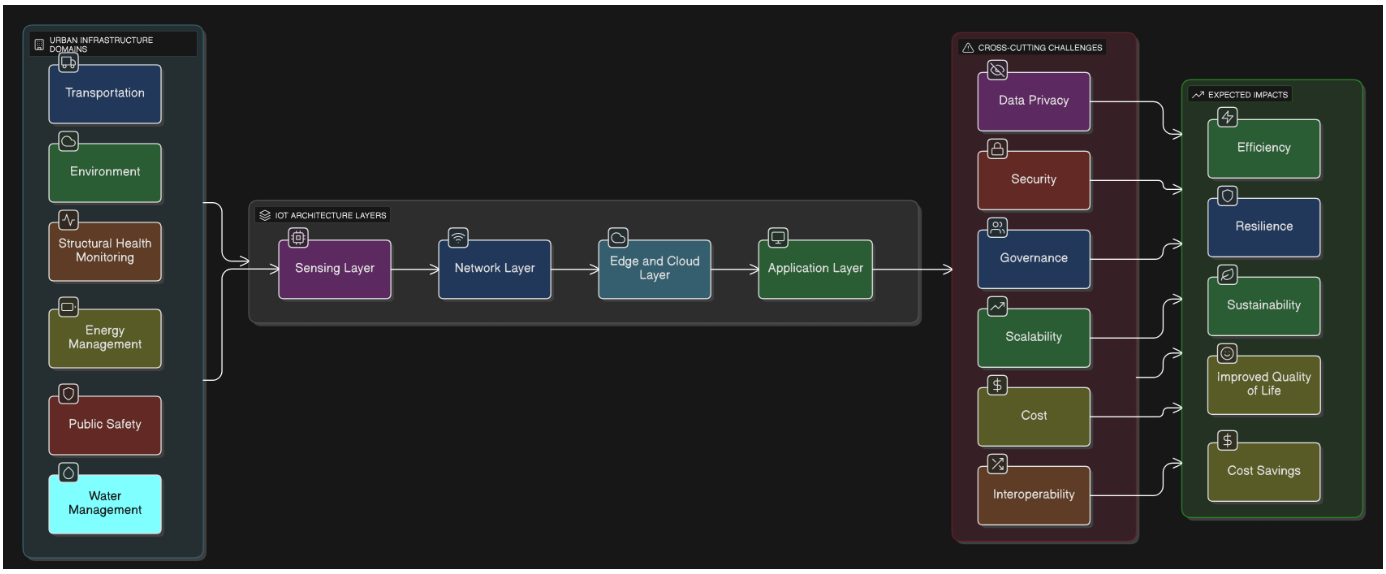

Figure 1. Conceptual framework of IoT-based urban infrastructure integrating application domains, architectural layers, cross-cutting challenges, and expected impacts.

Table 7. Matrix-based synthesis of IoT applications and cross-cutting challenges across urban infrastructure domains

Urban Domain ↓ / Challenge →	Security	Interoperability	Scalability	Governance	Sustainability
Transportation	✓✓	✓✓✓	✓✓	✓	✓✓

Environmental Monitoring	✓	✓✓	✓✓✓	✓✓	✓✓✓
Smart Parking	✓	✓✓	✓	✓	✓
Structural Health Monitoring	✓✓✓	✓	✓✓	✓✓	✓✓
Smart City Platforms	✓✓✓	✓✓✓	✓✓✓	✓✓✓	✓✓

✓ = low emphasis
✓✓ = moderate
✓✓✓ = high emphasis

4. CHALLENGES AND FUTURE DIRECTIONS

4.1 High-Priority Challenges

Cyber security and data privacy are recognized to be the major issue related to the use of IoT in urban infrastructure, since there is a considerable amount of sensitive information generated through IoT-enabled systems. As expanded in the matrix synthesis analysis in Table 7, smart city platforms, transportation systems, and structural health monitoring systems have been found to be highly vulnerable to threats. The vulnerability of IoT systems to security risks has been caused by insecure communication systems and inadequate access control, which create spaces for possible security breaches and failures, thereby affecting public security and trust. The issue of interoperability has also been identified to be a big challenge in all dimensions related to urban infrastructure, since it has been identified that IoT systems are made and created through different hardware, software, and communication platforms. As identified in Table 7, there seems to be no space for interoperability in transportation systems and integrated smart city platforms, which demand highly inter-domain data interaction. Non-interoperability has resulted in difficulties in integrating systems, and hence there are concerns regarding scalability and sustainability in IoT systems. Most IoT applications have been identified to demonstrate promising results in pilots and small-scale implementations. Still, it has been identified to be a big challenge to develop IoT-based applications at the city scale. As identified in Table 7, the factor involving scalability and cost has been identified to be important in environmental and smart city platforms.

4.2 High-Priority Challenges

Proper data management is necessary to promote good data gathering, transfer, and usage in the IoT-based infrastructure for smart cities. The regulatory systems, however, remain outdated to some extent, causing uncertainty about data rights, data protection, and data transfer among government entities. Such challenges related to data management, as shown in Table 7, may create inefficiencies at the institutional level and thereby hamper the potential use of integrated smart city systems. Aside from the challenges mentioned above, human and institutional aspects greatly affect the success of IoT systems. Lack of technical knowledge, capacity, and unwillingness to adapt to the new infrastructure may hamper the use and effective implementation of the IoT systems. The challenge, although moderate according to Table 7, becomes more significant at the stage where the IoT projects transition to sustainable IoT infrastructure in a smart city.

Overall, the prioritization of challenges highlights that technical issues alone do not determine the success of IoT-based urban infrastructure. Instead, the interplay between cybersecurity, interoperability, economic feasibility, governance, and institutional capacity shapes the long-term viability of smart city initiatives. Addressing high-priority challenges while strengthening medium-priority enablers is therefore essential to achieve scalable, secure, and sustainable urban infrastructure systems.

5. FUTURE RESEARCH DIRECTIONS

5.1 Short- to Medium-Term Research Directions

The focus of future work should be on finding solutions to important technical issues that currently impede IoT-based urban infrastructure applications. Among these important research topics is IoT security and privacy, particularly targeting applications that require a high level of security, such as transportation, structural health monitoring, and comprehensive smart city systems. The research should target the design of efficient encryption algorithms, authentication methods, and real-time intrusion detection, particularly because IoT applications operate under resource-restricted environments. The other important area that warrants research is interoperability and standardization. In view of the different devices, platforms, and applications used, research should target standardized data representations, open communication protocols, and middleware tools that should make it possible to facilitate seamless exchanges between different domains of urban infrastructure systems. This is important, particularly to enable cross-sectorial applications, as highlighted in a conceptual framework (see Figure 1) and a matrix synthesis (see Table 7). The second area that warrants urgent research is the use of efficient scaling strategies. Low-power sensing, energy-efficient communication, and edge processing of IoT data should be pursued to realize low running costs without sacrificing performance. Cases that test large-scale IoT systems implementations in different environments should inform research on viable IoT scaling strategies.

5.2 Long-Term Strategic Research Directions

In addition to the current technological issues, a more holistic, interdisciplinary approach is recommended in future research. A possible trend in this context is the combination of artificial intelligence, edge intelligence, and IoT-based urban infrastructure to enable predictive analysis, autonomous decision-making, and adaptive behavior. Future research studies should analyze the role of IoT technologies using artificial intelligence in increasing the resilience of cities. The third possible research trend is the IoT research perspective in governance. As IoT technology develops in urban infrastructure, an increasing need is emerging to develop an appropriate technological framework to reconcile technological innovation in IoT with governance, ethic, and societal values. Future studies in this topic may help in analyzing the effects of IoT adoption on socio-economic aspects in urban communities. The final possible research trend is an IoT technical performance analysis technique in an economic, societal, and environmental perspective. A multidimensional analysis technique is critical to examine the actual performance of IoT technologies in urban infrastructure development to develop evidence-based urban policies.

6. THEORETICAL AND PRACTICAL IMPLICATIONS

6.1 Theoretical Implications

This review provides theoretical development in smart city and urban infrastructure studies through providing an integrated perspective on the adoption of IoT across various infrastructure domains. By synthesizing IoT applications using a uniform conceptual framework (Figure 1), this study provides advancement compared to literature that has often treated urban infrastructure systems as isolated technological silos. The framework proposed herein emphasizes the interdependencies between technological architectures, socio-technical challenges, and the sustainability of urban outcomes, supporting a more systemic understanding of IoT-enabled urban infrastructure. In addition, the review extends prior theoretical work by underscoring the role of cross-cutting challenges-such as cybersecurity, interoperability, and governance-that are central rather than peripheral implementation issues in determining IoT system effectiveness. Overall, matrix-based synthesis (Table 7) offers a structured analytical frame that future researchers can leverage to classify, compare, and evaluate IoT studies across diverse urban contexts. It therefore provides a transferable conceptual approach supporting theory development in IoT-driven smart city research.

6.2 Practical and Policy Implications

From a pragmatic standpoint, conceptual frameworks derived from this analysis provide real-world insights to urban designers, infrastructure managers, and tech developers engaged in smart city projects. Prioritizing key challenges, namely cybersecurity, compatibility, and scalability, implies that overall planning must be done in harmony with future needs for sustainable functionality rather than focusing on short-term pilots and research. More importantly, policymakers must consider this analysis in suggesting that overall governance models and regulation alignment are key to successful IoT adoption within all sectors of urban infrastructure. On another platform, this analysis offers insights to policymakers on informed data policies, streamlined procurement procedures, and interagency collaboration to optimize IoT return on investment. Equally important, this analysis advances a concept framework to be used in making decisions on IoT projects and structuring overall construction and development endeavors in relation to overall impact on sustainable efficiency, sustainability, and overall resilience within urban infrastructure. Lastly, in connecting with overall industry developers and professionals in this analysis, overall development must meet all related criteria to satisfy overall expectations within public sectors.

7. CONCULUSSION

This review has investigated the use of Internet of Things (IoT) technologies for the development of urban infrastructure by integrating research findings across several critical sectors, namely intelligent transportation networks, environmental sensing networks, intelligent parking solutions, structural health sensor networks, and holistic smart city solutions. The evidence reveals that the use of IoT technologies can provide significant benefits to the efficiency, sustainability, and resilience of the infrastructure of a smart city by utilizing the ability of these technologies for real-time data harvesting and intelligent decision mechanisms. Apart from summarizing specific technological solutions, the present study offers an extensive review and critical integration of technological architectures and the pervasive challenges associated across these disciplines. The present study offers a conceptual framework and matrix-based analysis strategy by integrating critical research across several disciplines and addresses the prevailing body of knowledge by identifying the dependent variables associated among the development of the Internet of Things and the governance mechanisms leading to sustainable development outcomes related to the infrastructure of a smart city. The outcomes of the present study suggest that the challenges associated with cybersecurity threats, compatibility, and scalability represent critical deterministic factors related to the long-term sustainability of the Internet of Things-based infrastructure development of a smart city. Furthermore, the future study suggests that the evidence and findings reported by the present study have critical significance and relevance to the development needs of a smart city and the need for a concerted approach across technological and governance strategies for ensuring the development of smart city solutions following the main priorities and challenges and enabling research across several disciplines and areas by focusing across critically important perspectives related to the needs of a smart city or sustainable infrastructure development solutions across these areas.

REFRENCES

[1] K. Leng and C.-F. Wu, "Traffic Management Optimization via IoT-Enhanced Cooperative Vehicle-Infrastructure Systems," *IEEE Internet Things J*, vol. 12, no. 4, pp. 3493–3501, Feb. 2025, doi: 10.1109/JIOT.2024.3419440.

[2] B. V. Jagdish, I. A, M. N. Vikas, A. M, and C. Naik, "Decentralised IoT Authentication using Blockchain and Machine Learning: The Trust Circle Framework," in *2025 International Conference on Inventive Computation Technologies (ICICT)*, IEEE, Apr. 2025, pp. 1765–1770. doi: 10.1109/ICICT64420.2025.11005150.

[3] N. E. H. Boubaker, K. Zarour, N. Guermouche, and D. Benmerzoug, "A Comprehensive Survey on Resource Management for IoT Applications in Edge-Fog-Cloud Environments," *IEEE Access*, vol. 13, pp. 111892–111925, 2025, doi: 10.1109/ACCESS.2025.3583584.

[4] S. Majumder, A. K. Roy, T. Mondal, and M. J. Deen, "Flexible Sensors for IoT-Based Health Monitoring," *IEEE Journal on Flexible Electronics*, vol. 4, no. 2, pp. 63–88, Feb. 2025, doi: 10.1109/JFLEX.2025.3538808.

[5] N. V. Golovastikov, N. L. Kazanskiy, and S. N. Khonina, "Optical Fiber-Based Structural Health Monitoring: Advancements, Applications, and Integration with Artificial Intelligence for Civil and Urban Infrastructure," *Photonics*, vol. 12, no. 6, p. 615, Jun. 2025, doi: 10.3390/photonics12060615.

[6] J. W. Kasubi, M. D.H, and G. D. Demewez, "A review on the Internet of Things and Big Data Analytics Based on Smart Cities," in *2021 International Conference on Artificial Intelligence and Smart Systems (ICAIS)*, IEEE, Mar. 2021, pp. 1352–1358. doi: 10.1109/ICAIS50930.2021.9395958.

[7] D. Sharma, P. Kushwaha, Shorya, A. Verma, and A. Chaudhary, "Harnessing IoT and Machine Learning for Efficient Water Management in Urban Infrastructure," in *2025 International Conference on Pervasive Computational Technologies (ICPCT)*, IEEE, Feb. 2025, pp. 70–74. doi: 10.1109/ICPCT64145.2025.10940600.

[8] P. Saikia, B. Sahu, G. Prasad, S. Kumar, S. Suman, and K. Kumar, "Smart Infrastructure Systems: A Review of IoT-Enabled Monitoring and Automation in Civil and Agricultural Engineering," *Asian Journal of Research in Computer Science*, vol. 18, no. 4, pp. 24–44, Mar. 2025, doi: 10.9734/ajrcos/2025/v18i4606.

[9] M. Joshika, R. Ashwin, S. H. Varshini, A. K. Jubair Ahamed, and B. Sakthikumar, "Smart Water Management System For Rural And Urban Infrastructure Using Iot," in *2025 3rd International Conference on Advancements in Electrical, Electronics, Communication, Computing and Automation (ICAECA)*, IEEE, Apr. 2025, pp. 1–6. doi: 10.1109/ICAECA63854.2025.11012582.

[10] Ayush, P. Singh, P. Jain, V. Saini, K. Kumari, and P. Kumar Bajaj, "Enhancing Smart City Infrastructure Through IoT-Enabled Predictive Maintenance and Real-Time Data Analytics," in *2024 International Conference on Progressive Innovations in Intelligent Systems and Data Science (ICPIDS)*, IEEE, Dec. 2024, pp. 129–137. doi: 10.1109/ICPIDS65698.2024.00029.

[11] M. Chauhan and D. R. Sahoo, "Towards a Greener Tomorrow: Exploring the Potential of AI, Blockchain, and IoT in Sustainable Development," *Nature Environment and Pollution Technology*, vol. 23, no. 2, pp. 1105–1113, Jun. 2024, doi: 10.46488/NEPT.2024.v23i02.044.

[12] T. Magara and Y. Zhou, "Internet of Things (IoT) of Smart Homes: Privacy and Security," *Journal of Electrical and Computer Engineering*, vol. 2024, pp. 1–17, Apr. 2024, doi: 10.1155/2024/7716956.

[13] A. M. Yusof, N. Hussin, K. A. Azman, N. Amran, S. C. Daud, and N. R. Tarmuchi, "The Internet of Things (IOT): Impacts on Information Management Field," *International Journal of Academic Research in Business and Social Sciences*, vol. 10, no. 11, Dec. 2020, doi: 10.6007/IJARBSS/v10-i11/8197.

[14] Y. Bin Zikria, R. Ali, M. K. Afzal, and S. W. Kim, "Next-Generation Internet of Things (IoT): Opportunities, Challenges, and Solutions," *Sensors*, vol. 21, no. 4, p. 1174, Feb. 2021, doi: 10.3390/s21041174.

[15] Y. A. Alsahib S.aldeen and K. N. Qureshi, "New Trends in Internet of Things, Applications, Challenges, and Solutions," *TELKOMNIKA (Telecommunication Computing Electronics and Control)*, vol. 16, no. 3, p. 1114, Jun. 2018, doi: 10.12928/telkomnika.v16i3.8483.

[16] J. Bzai *et al.*, "Machine Learning-Enabled Internet of Things (IoT): Data, Applications, and Industry Perspective," *Electronics (Basel)*, vol. 11, no. 17, p. 2676, Aug. 2022, doi: 10.3390/electronics11172676.

[17] L. H. Fang and D. Yonggui, "Definition, Challenges and Future Research for Internet of Things," *Journal of Computing and Natural Science*, pp. 216–226, Oct. 2023, doi: 10.53759/181X/JCNS202303020.

[18] F. Campagnaro *et al.*, "Monitoring the Venice Lagoon: An IoT Cloud-Based Sensor Network Approach," *IEEE Journal of Oceanic Engineering*, vol. 50, no. 2, pp. 570–582, Apr. 2025, doi: 10.1109/JOE.2024.3459483.

[19] C.-M. Rosca and A. Stancu, "Integration of AI in Self-Powered IoT Sensor Systems," *Applied Sciences*, vol. 15, no. 13, p. 7008, Jun. 2025, doi: 10.3390/app15137008.

[20] F. Amin, R. Abbasi, A. Mateen, M. Ali Abid, and S. Khan, "A Step toward Next-Generation Advancements in the Internet of Things Technologies," *Sensors*, vol. 22, no. 20, p. 8072, Oct. 2022, doi: 10.3390/s22208072.

[21] V. S. Milankumar Rana, "Quantum-Edge Synergy: A Novel Framework for Real-Time IoT Analytics Beyond Cloud and Edge Computing," *Journal of Information Systems Engineering and Management*, vol. 10, no. 37s, pp. 925–935, Mar. 2025, doi: 10.52783/jisem.v10i37s.6746.

[22] B. Et-Taibi, M. R. Abid, E.-M. Boufounas, and D. Benhaddou, "Cloud and Edge based Smart Agriculture: A Real-World Deployment," in *2024 International Conference on Circuit, Systems and Communication (ICCSC)*, IEEE, Jun. 2024, pp. 1–6. doi: 10.1109/ICCSC62074.2024.10617136.

[23] R. Krishnamurthi, A. Kumar, D. Gopinathan, A. Nayyar, and B. Qureshi, "An Overview of IoT Sensor Data Processing, Fusion, and Analysis Techniques," *Sensors*, vol. 20, no. 21, p. 6076, Oct. 2020, doi: 10.3390/s20216076.
[24] M. Ashfaq and S. Nur, "IoT Sensor Networks- Orchestrating Connectivity, Efficiency, and Intelligence Across Diverse Domains," *International Journal of Innovative Research in Computer Science and Technology*, vol. 12, no. 3, pp. 154–161, May 2024, doi: 10.55524/ijircst.2024.12.3.26.
[25] D. Rocha, G. Teixeira, E. Vieira, J. Almeida, and J. Ferreira, "A Modular In-Vehicle C-ITS Architecture for Sensor Data Collection, Vehicular Communications and Cloud Connectivity," *Sensors*, vol. 23, no. 3, p. 1724, Feb. 2023, doi: 10.3390/s23031724.
[26] I. Ficili, M. Giacobbe, G. Tricomi, and A. Puliafito, "From Sensors to Data Intelligence: Leveraging IoT, Cloud, and Edge Computing with AI," *Sensors*, vol. 25, no. 6, p. 1763, Mar. 2025, doi: 10.3390/s25061763.
[27] M. Babar, M. A. Jan, X. He, M. U. Tariq, S. Mastorakis, and R. Alturki, "An Optimized IoT-Enabled Big Data Analytics Architecture for Edge–Cloud Computing," *IEEE Internet Things J*, vol. 10, no. 5, pp. 3995–4005, Mar. 2023, doi: 10.1109/JIOT.2022.3157552.
[28] S. Liu and G. C. Polyzos, "SovereignEdge: A Context-Aware Cryptographic Architecture for Data Sovereignty in Mobile Edge–Fog–Cloud IoT Data Spaces," in *2025 8th World Conference on Computing and Communication Technologies (WCCCT)*, IEEE, Apr. 2025, pp. 166–175. doi: 10.1109/WCCCT65447.2025.11027965.
[29] R. Dogea, X. T. Yan, and R. Millar, "Implementation of an edge-fog-cloud computing IoT architecture in aircraft components," *MRS Commun*, vol. 13, no. 3, pp. 416–424, May 2023, doi: 10.1557/s43579-023-00364-z.
[30] K. Yelamarthi, M. S. Aman, and A. Abdelgawad, "An Application-Driven Modular IoT Architecture," *Wirel Commun Mob Comput*, vol. 2017, pp. 1–16, 2017, doi: 10.1155/2017/1350929.
[31] M. Visuwasam L, A. Balakrishna, N. S R, and K. V, "Level-6 Automated IoT integrated with Artificial Intelligence Based Big Data-Driven Dynamic Vehicular Traffic Control System," *EAI Endorsed Transactions on Energy Web*, p. 164176, Jul. 2018, doi: 10.4108/eai.13-7-2018.164176.
[32] G. Chandrasekaran, P. S, R. N, H. A, D. K. N, and A. S, "Iot-Based Traffic Control for Emergency Services in Smart Transportation System," in *2025 International Conference on Inventive Computation Technologies (ICICT)*, IEEE, Apr. 2025, pp. 1844–1850. doi: 10.1109/ICICT64420.2025.11005044.
[33] A. C. S. Sheela, B. S. Ahamed, D. Poornima, and C. S. A. C, "Integration of Wireless Sensor Networks with IoT in Smart Transportation Systems and Traffic Management," in *2023 International Conference on Emerging Research in Computational Science (ICERCS)*, IEEE, Dec. 2023, pp. 1–6. doi: 10.1109/ICERCS57948.2023.10433998.
[34] A. P. Naveen, M. C. Monisha, T. Shanmugapriyan, and B. G. Geetha, "Smart Transportation Revolution: Adaptive Monitoring with Squeeze and Excitation Networks," in *2025 International Conference on Advanced Computing Technologies (ICoACT)*, IEEE, Mar. 2025, pp. 1–6. doi: 10.1109/ICoACT63339.2025.11005183.
[35] O. Igorevich Rozhdestvenskiy and E. Poornima, "Enabling Sustainable Urban Transportation with Predictive Analytics and IoT," *MATEC Web of Conferences*, vol. 392, p. 01179, Mar. 2024, doi: 10.1051/matecconf/202439201179.
[36] R. G, A. A. Lakshmi, R. B. Revathi, SK. A. Babu, R. G. Bodkhe, and H. J. Aljawawdeh, "A Smart RFID Based Automatic Toll Booth Management System Using Artificial Intelligence (AI) and Internet of Things Technologies," in *2024 International Conference on Innovative Computing, Intelligent Communication and Smart Electrical Systems (ICSES)*, IEEE, Dec. 2024, pp. 1–6. doi: 10.1109/ICSES63760.2024.10910827.
[37] N. Sutisna *et al.*, "FlexPay: Towards Cloud Based Automatic Number Plate Recognition System," in *2024 International Symposium on Intelligent Signal Processing and Communication Systems (ISPACS)*, IEEE, Dec. 2024, pp. 1–5. doi: 10.1109/ISPACS62486.2024.10868117.
[38] S. Seid, M. Zennaro, M. Libsie, E. Pietrosemoli, and P. Manzoni, "A Low Cost Edge Computing and LoRaWAN Real Time Video Analytics for Road Traffic Monitoring," in *2020 16th International Conference on Mobility, Sensing and Networking (MSN)*, IEEE, Dec. 2020, pp. 762–767. doi: 10.1109/MSN50589.2020.00130.
[39] N. Chen and Y. Chen, "Anomalous Vehicle Recognition in Smart Urban Traffic Monitoring as an Edge Service," *Future Internet*, vol. 14, no. 2, p. 54, Feb. 2022, doi: 10.3390/fi14020054.
[40] G. P. Panem, M. A. Begum, R. Maranan, A. Gaur, A. S. Yadav, and A. Dubey, "Next-Gen Smart Vehicle Number Plate Recognition with Dynamic Character Encoding for Lightning-Fast and Accurate Detection," in *2024 4th International Conference on Ubiquitous Computing and Intelligent Information Systems (ICUIS)*, IEEE, Dec. 2024, pp. 1292–1297. doi: 10.1109/ICUIS64676.2024.10866057.
[41] S. K. G. K, K. P. K, B. Muniyal, and M. Rajarajan, "Explainable Federated Framework for Enhanced Security and Privacy in Connected Vehicles Against Advanced Persistent Threats," *IEEE Open Journal of Vehicular Technology*, vol. 6, pp. 1438–1463, 2025, doi: 10.1109/OJVT.2025.3576366.
[42] Olukunle Oladipupo Amoo, Femi Osasona, Akoh Atadoga, Benjamin Samson Ayinla, Oluwatoyin Ajoke Farayola, and Temitayo Oluwaseun Abrahams, "Cybersecurity threats in the age of IoT: A review of protective measures," *International Journal of Science and Research Archive*, vol. 11, no. 1, pp. 1304–1310, Feb. 2024, doi: 10.30574/ijsra.2024.11.1.0217.
[43] H. Altaleb and R. Zoltán, "Addressing Cybersecurity Challenges in 5G-enabled IoT and Critical Infrastructures: A Comprehensive Overview," in *2023 IEEE 27th International Conference on Intelligent Engineering Systems (INES)*, IEEE, Jul. 2023, pp. 000131–000136. doi: 10.1109/INES59282.2023.10297774.
[44] C. Wheelus and X. Zhu, "IoT Network Security: Threats, Risks, and a Data-Driven Defense Framework," *IoT*, vol. 1, no. 2, pp. 259–285, Oct. 2020, doi: 10.3390/iot1020016.
[45] S. Bharati and P. Podder, "Machine and Deep Learning for IoT Security and Privacy: Applications, Challenges, and Future Directions," *Security and Communication Networks*, vol. 2022, pp. 1–41, Aug. 2022, doi: 10.1155/2022/8951961.
[46] M. Dündar, "The Integration of IoT, AI, and Machine Learning in Urban Systems," *Next Frontier For Life Sciences and AI*, vol. 8, no. 1, p. 185, Nov. 2024, doi: 10.62802/860ded41.
[47] Dr. G. Tamrakar, Dr. R. Sharma, and S. Rohilla, "Smart IoT-Based Air Quality Monitoring and Alert System for Urban Environments," *Int J Environ Sci*, pp. 628–633, Apr. 2025, doi: 10.64252/hdrg5v49.

[48] K. Chatterjee *et al.*, "Ecosense: a revolution in urban air quality forecasting for smart cities," *BMC Res Notes*, vol. 18, no. 1, p. 62, Feb. 2025, doi: 10.1186/s13104-025-07099-1.

[49] H. M. Forhad *et al.*, "IoT based real-time water quality monitoring system in water treatment plants (WTPs)," *Heliyon*, vol. 10, no. 23, p. e40746, Dec. 2024, doi: 10.1016/j.heliyon.2024.e40746.

[50] J. M. Taamté *et al.*, "Real-time air quality monitoring based on locally developed unmanned aerial vehicle and low-cost smart electronic device," *Journal of Instrumentation*, vol. 19, no. 05, p. P05036, May 2024, doi: 10.1088/1748-0221/19/05/P05036.

[51] M. Flores-Iwasaki, G. A. Guadalupe, M. Pachas-Caycho, S. Chapa-Gonza, R. C. Mori-Zabarburú, and J. C. Guerrero-Abad, "Internet of Things (IoT) Sensors for Water Quality Monitoring in Aquaculture Systems: A Systematic Review and Bibliometric Analysis," *AgriEngineering*, vol. 7, no. 3, p. 78, Mar. 2025, doi: 10.3390/agriengineering7030078.

[52] Y. Singh and T. Walingo, "Smart Water Quality Monitoring with IoT Wireless Sensor Networks," *Sensors*, vol. 24, no. 9, p. 2871, Apr. 2024, doi: 10.3390/s24092871.

[53] A. Dharshan, P. Kumar, S. Ravimaran, and U. Srinivasulu Reddy, "LSTM based Soft-Sensor for Estimating Nitrate Concentration in Aquaponics pond," in *2024 3rd International Conference for Innovation in Technology (INOCON)*, IEEE, Mar. 2024, pp. 1–8. doi: 10.1109/INOCON60754.2024.10511936.

[54] H. Wang, Y. Liu, C. Zhao, J. He, W. Ding, and X. Chen, "CaliFormer: Leveraging Unlabeled Measurements to Calibrate Sensors with Self-supervised Learning," in *Adjunct Proceedings of the 2023 ACM International Joint Conference on Pervasive and Ubiquitous Computing & the 2023 ACM International Symposium on Wearable Computing*, New York, NY, USA: ACM, Oct. 2023, pp. 743–748. doi: 10.1145/3594739.3612917.

[55] T. Blinova, S. Singh Chauhan, T. Singla, S. Bansal, A. Mittal, and V. S. Yellanki, "Performance Evaluation of IoT Sensors in Urban Air Quality Monitoring: Insights from the IoT Sensor Performance Test," *BIO Web Conf*, vol. 86, p. 01088, Jan. 2024, doi: 10.1051/bioconf/20248601088.

[56] A. Sinha and D. Das, "SNRepair: Systematically Addressing Sensor Faults and Self-Calibration in IoT Networks," *IEEE Sens J*, vol. 23, no. 13, pp. 14915–14922, Jul. 2023, doi: 10.1109/JSEN.2023.3277493.

[57] M. Taştan, "Machine Learning–Based Calibration and Performance Evaluation of Low-Cost Internet of Things Air Quality Sensors," *Sensors*, vol. 25, no. 10, p. 3183, May 2025, doi: 10.3390/s25103183.

[58] S. Ali, F. Alam, K. M. Arif, and J. Potgieter, "Low-Cost CO Sensor Calibration Using One Dimensional Convolutional Neural Network," *Sensors*, vol. 23, no. 2, p. 854, Jan. 2023, doi: 10.3390/s23020854.

[59] S. De Vito *et al.*, "A Global Multiunit Calibration as a Method for Large-Scale IoT Particulate Matter Monitoring Systems Deployments," *IEEE Trans Instrum Meas*, vol. 73, pp. 1–16, 2024, doi: 10.1109/TIM.2023.3331428.

[60] N. V. S. R. Nalakurthi *et al.*, "Challenges and Opportunities in Calibrating Low-Cost Environmental Sensors," *Sensors*, vol. 24, no. 11, p. 3650, Jun. 2024, doi: 10.3390/s24113650.

[61] A. M. S. V Sushma, A. Aswini Priyanka, A. N. G. Lakshmi, N. Khatri, and H. Sharma, "Integrated IoT-Based Smart Home Security System: Real-Time Hazard Detection and Alerts Using Multi-Sensor Fusion," in *2024 International Conference on Intelligent & Innovative Practices in Engineering & Management (IIPEM)*, IEEE, Nov. 2024, pp. 1–6. doi: 10.1109/IIPEM62726.2024.10925672.

[62] A. Krishna, B. Yadav, D. Prakash, and R. K. Dwivedi, "Designing A Fall Detection System for Elderly People in Smart Healthcare IoT Using Multi Sensor Data Fusion," in *2024 International Conference on Artificial Intelligence and Quantum Computation-Based Sensor Application (ICAIQSA)*, IEEE, Dec. 2024, pp. 1–7. doi: 10.1109/ICAIQSA64000.2024.10882340.

[63] K. Nesa, J. Akhter, M. M. Hassain, and M. A. Kader, "Image Processing and IoT Based Smart Parking Slot Detection and Notification System," in *2025 International Conference on Electrical, Computer and Communication Engineering (ECCE)*, IEEE, Feb. 2025, pp. 1–6. doi: 10.1109/ECCE64574.2025.11014054.

[64] B. Zheng, S. Tian, C. Rao, Q. Wang, C. Liang, and B. Tan, "Wireless Smart Greenhouse Management System Based on Multi-sensor of IoT," in *2023 IEEE 3rd International Conference on Electronic Communications, Internet of Things and Big Data (ICEIB)*, IEEE, Apr. 2023, pp. 95–99. doi: 10.1109/ICEIB57887.2023.10170112.

[65] A. E. Hamza *et al.*, "Design and implement WSN/IoT smart parking management system using microcontroller," *International Journal of Electrical and Computer Engineering (IJECE)*, vol. 10, no. 3, p. 3108, Jun. 2020, doi: 10.11591/ijece.v10i3.pp3108-3115.

[66] W. Zhai, "Design of NarrowBand-IoT Oriented Wireless Sensor Network in Urban Smart Parking," *International Journal of Online and Biomedical Engineering (iJOE)*, vol. 13, no. 12, pp. 116–126, Dec. 2017, doi: 10.3991/ijoe.v13i12.7886.

[67] M. M. Ahmed *et al.*, "Integrating IoT Technologies for Smart Parking Management: A Cost-Effective System with Telegram-Based Real-Time Alerts," in *2024 IEEE 22nd Student Conference on Research and Development (SCOReD)*, IEEE, Dec. 2024, pp. 670–674. doi: 10.1109/SCOReD64708.2024.10872700.

[68] L. Lou, Q. Li, Z. Zhang, R. Yang, and W. He, "An IoT-Driven Vehicle Detection Method Based on Multisource Data Fusion Technology for Smart Parking Management System," *IEEE Internet Things J*, vol. 7, no. 11, pp. 11020–11029, Nov. 2020, doi: 10.1109/JIOT.2020.2992431.

[69] M.Tamilselvi, "IoT-Driven Smart Parking with LoRaWAN and Magnetic Sensors for Advanced Vehicle Detection," in *2025 6th International Conference on Intelligent Communication Technologies and Virtual Mobile Networks (ICICV)*, IEEE, Jun. 2025, pp. 1283–1287. doi: 10.1109/ICICV64824.2025.11085745.

[70] M. Fischer, M. Guggenberger, and T. Ussmueller, "A Smart Parking Sensor with Multi-purpose Antenna for Car Detection and Sensor Charging," in *2020 50th European Microwave Conference (EuMC)*, IEEE, Jan. 2021, pp. 808–811. doi: 10.23919/EuMC48046.2021.9338176.

[71] S. S. Shankar *et al.*, "IoT-based parking surveillance scheme: Emerging a smart, effective, and secured solution for urban parking management and performance improvement," *MATEC Web of Conferences*, vol. 392, p. 01105, Mar. 2024, doi: 10.1051/matecconf/202439201105.

[72] A. E. Dwiputra, H. Khoswanto, R. Sutjiadi, and R. Lim, "IoT-Based Car's Parking Monitoring System," *MATEC Web of Conferences*, vol. 164, p. 01002, Apr. 2018, doi: 10.1051/matecconf/201816401002.

[73] G. Fertitta, W. Yang, A. Costanza, C. Martino, F. Macaluso, and D. Patanè, "Design and test of a Smart Sensor Box for structural and seismological monitoring with a high-performance QMEMS accelerometer," in *2024 IEEE International Workshop on Metrology for Industry 4.0 & IoT (MetroInd4.0 & IoT)*, IEEE, May 2024, pp. 541–546. doi: 10.1109/MetroInd4.0IoT61288.2024.10584235.

[74] M. Sidorov, J. H. Khor, P. V. Nhut, Y. Matsumoto, and R. Ohmura, "A Public Blockchain-Enabled Wireless LoRa Sensor Node for Easy Continuous Unattended Health Monitoring of Bolted Joints: Implementation and Evaluation," *IEEE Sens J*, vol. 20, no. 21, pp. 13057–13065, Nov. 2020, doi: 10.1109/JSEN.2020.3001870.

[75] L. Iacussi, P. Chiariotti, and A. Cigada, "AI-Enhanced IoT System for Assessing Bridge Deflection in Drive-By Conditions," *Sensors*, vol. 25, no. 1, p. 158, Dec. 2024, doi: 10.3390/s25010158.

[76] Sayali. R. Kokane and P. Jadhav, "Real Time Monitoring of Bridge by Using Sensor Technology with Concentration on Deflection Identification," in *2025 1st International Conference on AIML-Applications for Engineering & Technology (ICAET)*, IEEE, Jan. 2025, pp. 1–5. doi: 10.1109/ICAET63349.2025.10932156.

[77] A. Abdelgawad and K. Yelamarthi, "Structural health monitoring: Internet of things application," in *2016 IEEE 59th International Midwest Symposium on Circuits and Systems (MWSCAS)*, IEEE, Oct. 2016, pp. 1–4. doi: 10.1109/MWSCAS.2016.7870118.

[78] C. A. Ng, C. Pozzi, S. Lyon, M. Inalpolat, C. Niezrecki, and Y. Luo, "IoT acoustic sensor design and antenna selection for a wind turbine structural health monitoring system," in *NDE 4.0, Predictive Maintenance, Communication, and Energy Systems: The Digital Transformation of NDE II*, N. G. Meyendorf, C. Niezrecki, and S. Farhangdoust, Eds., SPIE, May 2024, p. 10. doi: 10.1117/12.3010478.

[79] A. Abdelgawad and K. Yelamarthi, "Internet of Things (IoT) Platform for Structure Health Monitoring," *Wirel Commun Mob Comput*, vol. 2017, pp. 1–10, 2017, doi: 10.1155/2017/6560797.

[80] A. R. Al-Ali *et al.*, "An IoT-Based Road Bridge Health Monitoring and Warning System," *Sensors*, vol. 24, no. 2, p. 469, Jan. 2024, doi: 10.3390/s24020469.

[81] X. Tong, H. Yang, L. Wang, and Y. Miao, "The Development and Field Evaluation of an IoT System of Low-Power Vibration for Bridge Health Monitoring," *Sensors*, vol. 19, no. 5, p. 1222, Mar. 2019, doi: 10.3390/s19051222.

[82] K. Chaturvedi and T. H. Kolbe, "Towards Establishing Cross-Platform Interoperability for Sensors in Smart Cities," *Sensors*, vol. 19, no. 3, p. 562, Jan. 2019, doi: 10.3390/s19030562.

[83] G. Kambala, "Enhancing IoT Data Exchange and Security through a Multi-Domain Interoperability Framework: Integrating Zigbee Network with Microsoft Azure IoT Platform," in *2025 Global Conference in Emerging Technology (GINOTECH)*, IEEE, May 2025, pp. 1–7. doi: 10.1109/GINOTECH63460.2025.11076962.

[84] O. B. Mora-Sanchez, E. Lopez-Neri, E. J. Cedillo-Elias, E. Aceves-Martinez, and V. M. Larios, "Validation of IoT Infrastructure for the Construction of Smart Cities Solutions on Living Lab Platform," *IEEE Trans Eng Manag*, vol. 68, no. 3, pp. 899–908, Jun. 2021, doi: 10.1109/TEM.2020.3002250.

[85] E. Patti and A. Acquaviva, "IoT platform for Smart Cities: Requirements and implementation case studies," in *2016 IEEE 2nd International Forum on Research and Technologies for Society and Industry Leveraging a better tomorrow (RTSI)*, IEEE, Sep. 2016, pp. 1–6. doi: 10.1109/RTSI.2016.7740618.

[86] V. Pranavasri *et al.*, "Scalable and Interoperable Distributed Architecture for IoT in Smart Cities," in *2023 IEEE 9th World Forum on Internet of Things (WF-IoT)*, IEEE, Oct. 2023, pp. 01–06. doi: 10.1109/WF-IoT58464.2023.10539501.

[87] J. N. S. Rubí and P. R. de Lira Gondim, "IoT-based platform for environment data sharing in smart cities," *International Journal of Communication Systems*, vol. 34, no. 2, Jan. 2021, doi: 10.1002/dac.4515.

[88] M. W. Iqbal, K. Khaliq, N. A. Al-Dmour, M. Aqeel, N. Ali, and K. Hamid, "Internet of Things (IoT) in Smart Cities: A Statistical Survey," in *2023 International Conference on Business Analytics for Technology and Security (ICBATS)*, IEEE, Mar. 2023, pp. 1–6. doi: 10.1109/ICBATS57792.2023.10111206.

[89] A. Morelli, L. Campioni, N. Fontana, N. Suri, and M. Tortonesi, "A Federated Platform to Support IoT Discovery in Smart Cities and HADR Scenarios," in *2020 Federated Conference on Computer Science and Information Systems*, Polskie Towarzystwo Informatyczne, Sep. 2020, pp. 511–519. doi: 10.15439/2020F48.

[90] E. Patti *et al.*, "Combining BIM, GIS, and IoT to Foster Energy Management and Simulation in Smart Cities," 2021, pp. 425–447. doi: 10.4018/978-1-7998-7091-3.ch019.