



An integrated AI-IoT framework for urban pollution source detection and sustainable Smart-City Governance



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Abstract

Urban air pollution remains a major challenge to sustainable city development because traditional monitoring systems have limited capacity to address complex and dynamic urban environments. Although Artificial Intelligence (AI) and Internet of Things (IoT) technologies have demonstrated considerable potential for environmental monitoring, existing approaches often emphasize individual technical capabilities while giving limited attention to governance transparency, ethical deployment, and sustainability alignment. This study proposes an integrated AI-IoT conceptual framework for urban pollution source detection and sustainable smart-city governance. The framework integrates multi-source environmental sensing, data processing, AI-driven forecasting and pollution source attribution, intelligent decision support, ethical AI governance, and Sustainable Development Goal (SDG) alignment within a unified six-layer architecture. Its conceptual grounding is assessed through structured literature mapping, comparative analysis of existing AI-based urban monitoring frameworks, and case-study mapping using a published IoT-enabled environmental monitoring application. The framework establishes an end-to-end pathway connecting environmental observations with pollution intelligence, policy-oriented decision support, responsible governance, and measurable sustainability outcomes. It also identifies key implementation challenges involving data privacy, algorithmic bias, explainability, interoperability, scalability, and deployment constraints. The proposed architecture provides a structured foundation for future implementation and empirical evaluation of intelligent, ethical, and sustainability-oriented urban pollution management systems.

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INTRODUCTION

Air pollution remains a major environmental and public-health challenge, particularly in rapidly urbanizing regions where industrialization, transportation, and energy consumption intensify emissions. Multiple pollution sources and complex spatiotemporal patterns complicate monitoring, source identification, and mitigation [1]. Conventional fixed monitoring stations provide reliable measurements but face limitations in spatial

coverage and deployment costs. IoT sensors, mobile sensing, remote sensing, and open environmental data enable more distributed and continuous monitoring [2]. Artificial Intelligence (AI) further supports pollution forecasting, hotspot and anomaly detection, source attribution, and decision support, transforming environmental data into actionable intelligence. However, effective smart-city pollution management also requires explainable AI, responsible governance, stakeholder

participation, system interoperability, and sustainability alignment. Integrating these dimensions enables transparent, accountable, and coordinated urban decision-making while linking technological capabilities with governance and sustainability priorities [3, 4, 5, 6].

Literature Review

Previous studies demonstrate the effectiveness of IoT-enabled sensing and AI for continuous environmental monitoring, pollution forecasting, anomaly detection, hotspot identification, and source-related analysis. Recent AI-IoT systems integrate sensing, communication, cloud or edge computing, and intelligent analytics [7, 8, 9, 10], while low-cost sensors, satellite imagery, mobile sensing, meteorological stations, and fixed monitoring infrastructure improve spatial and temporal monitoring coverage [11, 12, 13, 14].

Beyond monitoring, AI supports urban governance through reinforcement learning, predictive optimization, traffic management, emission reduction, and sustainable planning [15]. However, privacy, fairness, transparency, and accountability concerns necessitate explainable AI, federated learning, and responsible governance [16][17]. Integrating environmental regulation with energy, transportation, and waste-management services further supports sustainable urban ecosystems [18, 19, 20, 21, 22].

Recent studies have advanced integrated smart-city approaches. Bibri et al. [23] examined AIoT-enabled eco-city solutions, Yigitcanlar et al. [24] proposed a responsible urban AI governance framework, and Asha et al. [25] integrated IoT and AI for environmental toxicology and air-pollution monitoring.

Despite these contributions, existing studies do not fully establish an end-to-end pollution-intelligence architecture integrating heterogeneous sensing, forecasting, source attribution, explainable analytics, decision support, ethical governance, and sustainability outcomes. This gap motivates the proposed layered framework.

Research Gap

Despite advances in AI-IoT environmental monitoring, existing studies remain fragmented across sensing, analytics, governance, and sustainability, with limited integration of pollution source attribution, explainability, decision support, and responsible governance.

Although Bibri et al. [23] explored AIoT-enabled sustainable eco-cities and Yigitcanlar et al. [24] emphasized responsible urban AI governance, the reviewed literature lacks a comprehensive architecture explicitly linking heterogeneous sensing, data integration, pollution forecasting, source attribution, explainable analytics, policy-oriented decisions, ethical governance, and measurable sustainability outcomes.

Three interrelated gaps emerge: (1) a technical-to-analytical gap between heterogeneous sensing and AI-driven pollution intelligence; (2) an analytical-to-governance gap in translating AI outputs into explainable, accountable, and policy-oriented decisions; and (3) a governance-to-sustainability gap in connecting environmental intelligence with measurable sustainability objectives. The proposed six-layer framework addresses these gaps by integrating sensing, data processing, AI analytics, decision support, responsible governance, and SDG alignment, as summarized in Table 1.

Table 1. Research Gaps and Corresponding Framework Responses

Identified integration gap	Limitation in reviewed approaches	Proposed framework response	Relevant layers
Technical-to-analytical	Heterogeneous environmental data are not consistently connected to comprehensive pollution intelligence	Multi-source sensing, data standardization/fusion, forecasting, hotspot analysis, anomaly detection, and source attribution	Layers 1–3
Analytical-to-governance	AI outputs are not consistently translated into explainable and accountable policy support	XAI, intelligent decision support, stakeholder participation, transparency and accountability	Layers 3–5
Governance-to-sustainability	Governance actions are not consistently linked to measurable sustainability objectives	SDG-oriented indicators and sustainability assessment integrated with governance outcomes	Layers 5–6
Cross-layer feedback	Monitoring, policy action and sustainability outcomes may operate as separate processes	Continuous feedback connects sensing, analytics, decisions, governance and sustainability outcomes	Layers 1–6

Scientific Justification

The proposed framework is scientifically justified by the need to connect environmental monitoring capabilities with responsible governance and measurable sustainability objectives. Multi-source sensing improves environmental coverage, while AI-based analytics supports pollution forecasting, hotspot detection, anomaly detection, and source attribution. However, translating these capabilities into effective urban interventions requires explainable outputs, informed decision support, and accountable governance.

A unified AI-IoT conceptual framework therefore provides a systematic foundation for integrating established technologies with governance principles and sustainability goals, supporting future implementation, policy development, and interdisciplinary research in intelligent urban environmental management.

Novelty

The novelty of this study lies in the architectural integration of pollution intelligence with responsible urban governance and sustainability, rather than in proposing a new AI algorithm. Building upon existing research in AIoT-enabled sustainable cities and responsible urban AI [23,24], the proposed framework introduces a pollution-specific end-to-end conceptual architecture that connects multi-source environmental sensing, data integration, AI-based forecasting and source attribution, explainable analytics, policy-oriented decision support, ethical governance, and SDG alignment.

More specifically, the framework addresses three integration challenges: (1) technical-to-analytical, linking heterogeneous sensing with pollution analytics; (2) analytical-to-governance, translating AI outputs into explainable and accountable decision support; and (3) governance-to-sustainability, linking interventions to sustainability targets and indicators. Together, these provide a structured pathway from environmental sensing to analysis, governance, and sustainability assessment.

The contribution represents a conceptual architectural synthesis rather than an empirically validated system. Its theoretical grounding is assessed through literature mapping, comparative framework analysis, and case-study mapping, while implementation and quantitative validation remain future work.

Research Questions

To address the identified research gap, this study investigates the following research questions:

RQ1: How can heterogeneous environmental sensing and AI-based analytics be systematically integrated to support urban pollution monitoring and source attribution?

RQ2: How can AI-generated environmental intelligence be translated into explainable, responsible, and stakeholder-oriented decision support for smart-city governance?

RQ3: How can urban pollution intelligence and governance processes be aligned with measurable sustainability objectives and relevant SDGs?

Contributions

The principal contributions of this study are:

- 1) an integrated six-layer AI-IoT conceptual architecture linking environmental sensing, data integration, AI analytics, decision support, responsible AI governance, and sustainability alignment;
- 2) explicit integration of pollution source attribution and explainable analytics within the environmental intelligence pipeline;
- 3) incorporation of privacy, fairness, transparency, accountability, stakeholder participation, and regulatory considerations into AI-enabled urban pollution governance; and
- 4) conceptual evaluation through literature mapping, comparative framework analysis, and case-study mapping, together with a roadmap for future implementation.

MATERIALS AND METHOD

This study adopts a conceptual research design to develop an integrated AI-IoT framework for urban pollution source detection and sustainable smart-city governance. The framework was developed through structured literature synthesis, comparative framework analysis, and conceptual case-study mapping to establish its theoretical grounding and practical relevance rather than empirical validation.

Research Design

The research design focuses on systematically integrating intelligent sensing, pollution analytics, source attribution, decision support, responsible AI governance, and sustainability within a coherent conceptual architecture. Unlike experimental research that evaluates model performance, this study synthesizes established capabilities and

previously reported applications to develop a theoretically grounded framework with potential practical relevance.

Structured Literature Synthesis

Relevant literature on AI-driven pollution monitoring, environmental sensing, source attribution, smart-city governance, and responsible AI was identified through Scopus, IEEE Xplore, ScienceDirect, SpringerLink, Web of Science, and Google Scholar. Search terms included “AI pollution detection,” “urban air quality monitoring,” “IoT environmental sensing,” “LSTM air pollution,” and “smart-city sustainability.”

The literature was screened for relevance and quality using the criteria in Table 2. From 100 initially identified studies, 48 were excluded after duplicate removal and preliminary relevance screening. The remaining 52 studies underwent title, abstract, and full-text assessment, from which 12 were excluded based on the eligibility criteria. Consequently, 40 high-relevance studies were included for framework development and analysis. These studies provided the evidence base for identifying key AI-IoT capabilities, integration gaps, governance requirements, and sustainability considerations incorporated into the proposed framework.

Framework Development Process

The proposed framework was developed through four iterative phases. First, the literature was analyzed to identify common architectural components and technological capabilities in AI-based environmental monitoring. Second, key limitations were identified, including fragmentation, limited governance integration, insufficient explainability, and weak sustainability alignment. Third, established AI, IoT, forecasting, and source-attribution capabilities were integrated

into the proposed conceptual architecture. Finally, responsible AI principles and SDG requirements were incorporated to strengthen governance and sustainability alignment.

AI Technique Selection and Data Requirements

The framework incorporates candidate AI techniques rather than experimentally selected models. Their suitability depends on the analytical task, data characteristics, spatiotemporal structure, interpretability requirements, computational resources, and deployment environment. Where model or system optimization is required, metaheuristic and hybrid optimization strategies may also provide mechanisms for exploring complex parameter spaces and improving solution quality [49]. LSTM/GRU and CNN-LSTM can support temporal and spatiotemporal forecasting, while Transformers may address longer dependencies and multimodal data.

For spatial analysis, CNNs can process gridded data, while GNNs can model connected monitoring stations or urban networks. Source attribution may employ clustering, PMF, CMB, or hybrid approaches, whereas autoencoders and Isolation Forest can support anomaly and event detection.

Computational requirements vary with model complexity, data volume, hardware, and deployment configuration. Therefore, model selection should consider predictive performance, computational efficiency, and interpretability. The suitability of each technique also depends on the characteristics of environmental data and the specific analytical objectives of the framework. Table 3 summarizes the candidate AI techniques, their data requirements, and key selection considerations

Table 2. Literature Inclusion and Exclusion Criteria

No.	Criteria Type	Inclusion Criteria	Exclusion Criteria
1	Publication Type	Peer-reviewed journal articles and conference papers	Non-peer-reviewed articles, editorials, blogs
2	Research Scope	Studies related to AI, IoT, smart cities, and sustainability governance	Studies unrelated to urban environmental applications
3	Methodological Contribution	Studies with conceptual or governance contributions	Studies with insufficient methodological detail
4	Publication Period	Studies published between 2020–2026; earlier foundational studies were also included	Older studies without clear foundational relevance to the framework
5	Language	English-language publications	Non-English publications

Note: The screening process involved title, abstract, and full-text review to ensure relevance and quality. The 40 selected studies formed the core evidence base for framework development, while additional references were cited to support contextual, methodological, and technical discussions throughout the manuscript.

Table 3. Candidate Techniques and Selection Requirements

Analytical Task	Candidate Techniques	Typical Input/Data Requirements	Key Selection Considerations
Pollution forecasting	LSTM/GRU; CNN-LSTM; Transformer	Historical pollutant concentrations, meteorological variables, traffic/emission data; time-stamped observations	Temporal dependency, data volume, forecasting horizon, computational resources
Spatial analysis and hotspot detection	CNN; GNN; spatial statistical methods	Georeferenced sensor observations, gridded pollution maps, monitoring-station networks, road/urban topology	Spatial representation, network structure, spatial resolution, interpretability, computational cost
Pollution source attribution	Clustering; PMF; CMB; hybrid approaches	Pollutant/species concentrations, source profiles, temporal and spatial measurements; contextual emission information	Availability of source profiles, chemical composition, interpretability, source complexity
Anomaly and event detection	Autoencoder; Isolation Forest; change-point methods	Multivariate environmental time series and representative normal-condition observations	Label availability, anomaly frequency, computational cost, real-time requirements
Explainable environmental intelligence	SHAP; LIME; feature importance	Trained predictive model, model inputs, predictions and relevant features	Model compatibility, local/global explanation needs, computational overhead, stakeholder interpretability

In practical implementation, candidate models should be assessed using task-specific predictive metrics alongside latency, memory requirements, robustness to noisy or missing sensor data, and scalability across heterogeneous urban environments. Final model selection should reflect deployment requirements rather than predictive accuracy alone.

Conceptual Framework Evaluation Strategy

- Literature Mapping:** Each framework component was mapped to peer-reviewed studies supporting AI, IoT, forecasting, source attribution, decision support, governance, and sustainability mechanisms in urban environmental applications. This mapping establishes the theoretical grounding of the proposed architecture.
- Comparative Framework Analysis:** The proposed architecture was compared with existing AI-IoT, environmental monitoring, sustainable smart-city, and responsible urban AI frameworks. The comparison examined environmental sensing, AI analytics, pollution source attribution, explainability, responsible AI governance, decision support, and sustainability linkage.
- Conceptual Case-Study Mapping:** The framework was mapped to a published IoT-enabled environmental monitoring application to assess correspondence between reported real-world capabilities and the proposed architecture. The mapping is interpretive and does not imply implementation or empirical validation of the complete six-layer framework. Operational performance, scalability, cost, interoperability, and governance feasibility

therefore remain subjects for future empirical evaluation.

RESULTS AND DISCUSSION

This study proposes a six-layer AI-IoT framework integrating environmental sensing, data processing, AI-driven pollution intelligence, decision support, responsible AI governance, and sustainability alignment. Figure 1 presents the proposed architecture and the interactions among its principal components.

Proposed AI-IoT Urban Pollution Governance Framework

The framework comprises six interconnected layers: (1) Data Acquisition, (2) Data Processing and Integration, (3) AI Analytics, (4) Intelligent Decision Support, (5) Ethical AI and Governance, and (6) Sustainability and SDG Alignment. Continuous feedback mechanisms are intended to support adaptive learning and long-term system optimization.

Layer 1: Data Acquisition (Multi-Source Environmental Sensing)

The first layer integrates heterogeneous environmental data from IoT sensors, fixed monitoring stations, mobile platforms, satellite observations, and other relevant urban data sources. Combining multiple sensing modalities can improve spatial and temporal coverage and provide a broader representation of pollution conditions than reliance on a single source. These data form the input for subsequent processing and intelligent analysis [26].

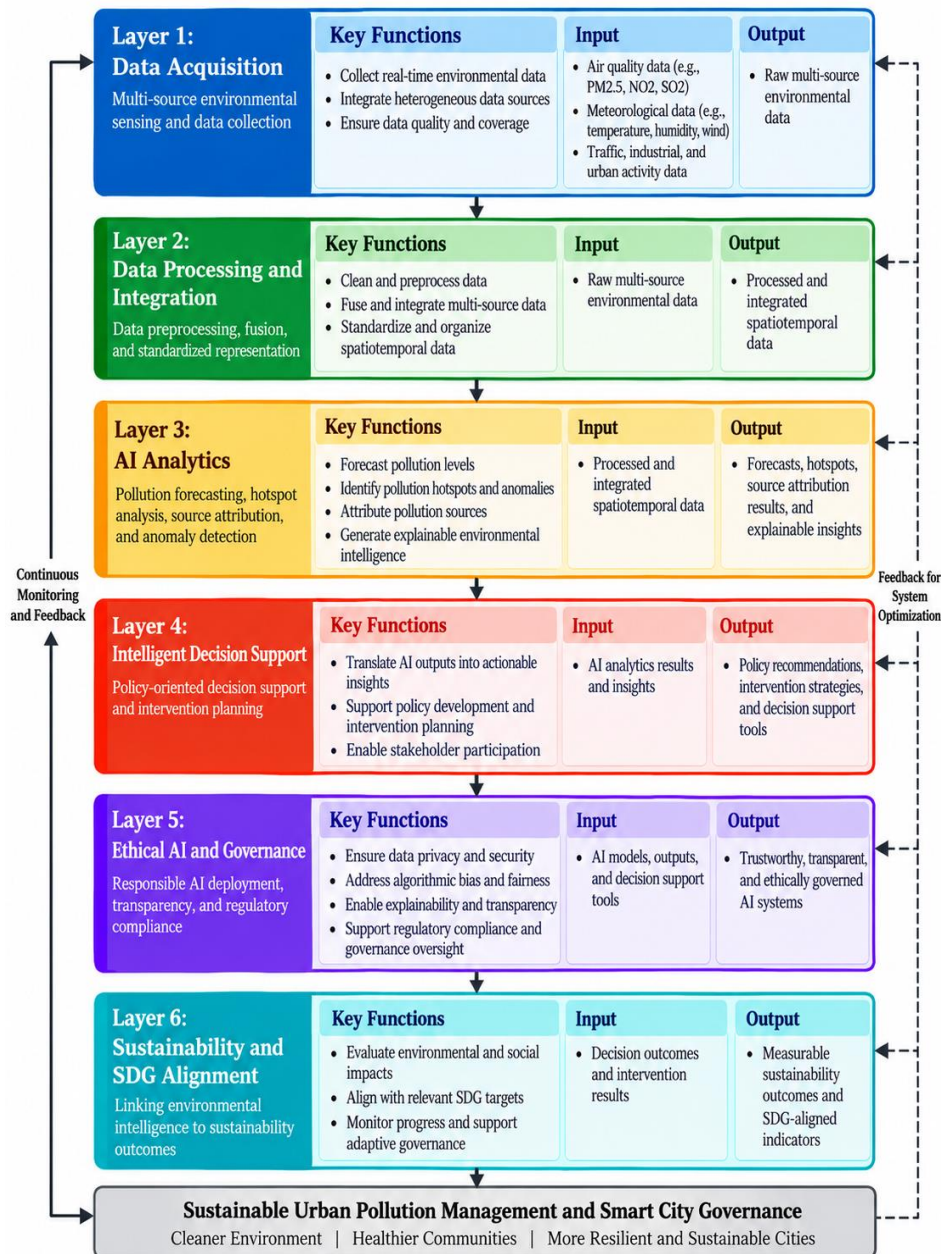


Figure 1. Proposed AI-IoT Framework for Urban Pollution Detection and Sustainable Governance

Layer 2: Data Processing and Integration

The second layer transforms heterogeneous environmental observations into standardized and usable data through cleaning, normalization, synchronization, fusion, and storage. Edge and cloud computing can support distributed processing according to latency, computational, and scalability requirements. This layer provides consistent and reliable inputs for AI-based environmental analysis [27][28].

Layer 3: AI-Driven Pollution Intelligence

The third layer transforms processed environmental data into pollution intelligence

through forecasting, hotspot analysis, anomaly detection, and source attribution. Candidate techniques include LSTM/GRU, CNN-LSTM, Transformers, CNNs, GNNs, autoencoders, Isolation Forest, clustering, PMF, and CMB, selected according to task requirements, performance, interpretability, and computational constraints. Image-based AI can extract visual features such as shape, texture, and color for automated analysis [50], while CNNs, graph-based learning, and geospatial methods support air-quality assessment and hotspot detection [4,9,26,51]. Clustering, receptor modeling, and deep learning can support pollution source

attribution [29-31]. Autoencoders and Isolation Forest enable anomaly detection in environmental and IoT data [52], while SHAP and LIME improve model interpretability and transparency [32].

Layer 4: Intelligent Decision Support

The fourth layer translates AI-generated pollution intelligence into actionable information for urban decision-making. Forecasts, hotspots, anomalies, and source-attribution results support alerts, dashboards, intervention planning, and policy assessment. Explainable AI further enhances the interpretability of analytical outputs for policymakers, environmental agencies, and stakeholders.

The architecture also supports adaptive traffic optimization, pollution-aware routing, urban zoning analysis, and public environmental education. Citizen engagement tools, including mobile applications and public dashboards, promote participatory, data-driven environmental governance.

Layer 5: Ethical AI and Governance

The fifth layer integrates responsible AI principles into urban environmental monitoring through privacy-preserving methods, fairness-aware learning, explainability, transparency, and governance accountability. These mechanisms address ethical concerns associated with intelligent urban surveillance and environmental monitoring systems.

Federated learning, edge computing, encryption, and privacy-by-design strategies mitigate data-exposure risks, while bias mitigation addresses unequal environmental representation in underserved communities. Explainable AI improves transparency by helping stakeholders understand model predictions and decisions. Regulatory compliance, stakeholder engagement, and governance oversight further support trustworthy and socially responsible AI implementation in smart-city ecosystems.

Layer 6: Sustainability and SDG Alignment

The sixth layer links pollution intelligence and governance actions to measurable sustainability objectives, particularly SDG 3 (Good Health and Well-being), SDG 11 (Sustainable Cities and Communities), and SDG 13 (Climate Action). It integrates sustainability considerations into environmental decision-making.

The framework supports SDG targets 3.9, 11.6, and 13.2 through pollution-risk reduction, urban air-quality management, and climate-responsive planning. Potential indicators include pollutant concentrations, population exposure, pollution-event frequency, source-specific emission trends, warning response time, and documented use of pollution intelligence in urban planning. Table 4 summarizes the framework's alignment with relevant SDG targets and measurable indicators for future implementation.

Interaction and Feedback Mechanism

Collectively, the six layers establish an end-to-end conceptual pathway from environmental observation to intelligent analysis, decision support, responsible governance, and sustainability assessment. Their integration distinguishes the proposed framework from approaches that address sensing, analytics, governance, or sustainability as largely separate functions.

Conceptual Framework Evaluation

The proposed framework was conceptually evaluated through three complementary approaches: literature mapping, comparative framework analysis, and case-study mapping. These approaches assess its theoretical grounding, architectural consistency, and correspondence with existing environmental monitoring capabilities rather than empirically validating its operational performance.

Table 4. Alignment of Framework Outputs with SDG Targets and Measurable Indicators

SDG target	Framework relevance	Example measurable indicators
SDG 3.9 – Reduce deaths and illnesses from pollution	Pollution forecasting, exposure assessment, early warning and source attribution	Pollutant concentration; population exposure; high-risk pollution events; warning response time
SDG 11.6 – Reduce cities' environmental impact, including air quality	Multi-source urban monitoring, hotspot detection and pollution management	PM _{2.5} and PM ₁₀ levels; spatial pollution hotspots; exceedance frequency; monitoring coverage
SDG 13.2 – Integrate climate measures into policies and planning	Emission intelligence and climate-responsive decision support	Source-specific emission trends; emission-reduction interventions; incorporation of environmental intelligence into urban/climate plans

Literature mapping connects the six framework layers with peer-reviewed studies covering AI, IoT, pollution forecasting, source attribution, decision support, responsible governance, and sustainability. This establishes the scientific foundations of the proposed architecture and identifies how existing capabilities contribute to its integration.

Table 5 summarizes the mapping by linking framework components to representative studies and highlighting their respective functions within the proposed architecture.

Integrating these previously fragmented capabilities into a unified pollution-intelligence architecture represents a key conceptual contribution of this study.

Comparative Framework Analysis

Comparative framework analysis examined the proposed architecture alongside existing AI-IoT, sustainable smart-city, and responsible urban AI frameworks, recognizing their complementary strengths in sensing, analytics, sustainability, and governance. Table 6 compares these frameworks across pollution-specific sensing, analytics, source attribution, explainability, governance, decision support, and sustainability alignment.

Pollution-specific IoT-AI systems [25,39,42] support sensing, analytics, and decision-making, with one incorporating privacy-preserving federated learning. However, they lack explicit integration of source attribution, explainability, governance, and sustainability within a unified architecture. The proposed framework builds on these capabilities by connecting environmental sensing and pollution intelligence with explainable governance decisions and sustainability assessment.

Conceptual Case-Study Mapping

A published IoT-enabled environmental monitoring application was mapped to the proposed architecture to examine correspondence between reported operational capabilities and the framework layers [25].

Table 7 maps reported case-study capabilities and additional implementation requirements to the proposed framework. This conceptual mapping illustrates architectural correspondences rather than empirical validation. Components related to explainability, ethical AI governance, stakeholder participation, and explicit SDG alignment are extensions of the proposed framework and should not be interpreted as capabilities implemented in the source case study. Their inclusion in the mapping indicates how the proposed architecture could extend an existing environmental monitoring system toward more transparent, governance-oriented, and sustainability-aligned urban environmental intelligence. The mapping links selected environmental monitoring capabilities to the proposed architecture and identifies additional requirements for full implementation.

Together, these three approaches provide conceptual support for the framework, demonstrating that its integrated capabilities are grounded in prior research while distinguishing conceptual evaluation from empirical validation.

Discussion

This section examines the framework's scientific contribution, practical applicability, deployment challenges, ethical implications, and sustainability relevance.

Table 5. Literature Mapping of the Proposed Framework Components

Framework component	Established capability	Supported Studies
Data Acquisition	Real-time IoT and distributed sensing, including dense low-cost sensor networks and cloud-connected multi-pollutant sensor arrays	[6,25,26,33,34]
Data Processing and Integration	Cloud-edge fusion, edge-based spatiotemporal preprocessing, multi-source data fusion, and scalable processing	[12,25,27,28,35,36]
AI Analytics	Forecasting, hotspot detection, source attribution, air-quality classification and prediction, and interpretable (SHAP/LIME) analytics	[5,8,19,25,29,30,32,37]
Intelligent Decision Support	Real-time alerts, policy simulation, mitigation-scenario testing, and urban optimization	[14,17,25,38,39]
Ethical AI & Governance	Explainability, fairness, privacy-preserving federated learning, and responsible urban AI governance	[16,24,40-42]
Sustainability & SDG Alignment	Sustainable governance, SDG alignment, and urban resilience	[43-48]

Table 6. Comparative Mapping of Related Frameworks and the Proposed Architecture

Study	Primary Scope	Data Acquisition	Data Processing & Integration	AI/Analytics	Intelligence Decision Support	Ethical AI and Governance	Sustainability and SDG Alignment
Popescu et al. [6]	AI-IoT environmental pollution monitoring	Explicit	Not central	Explicit	Limited	Limited	Addressed broadly
Bibri et al. [23]	AIoT-enabled smarter eco-cities	Supported	Not central	Explicit	Supported broadly	Addressed broadly	Explicit
Yigitcanlar et al. [24]	Responsible local-government AI	Not central	Not central	Supported broadly	Explicit	Explicit	Addressed broadly
Cavicchioli et al. [27]	Edge-cloud smart-city data analytics	Explicit	Not central	Explicit	Supported	Not central	Not explicit
Bokhari and Myeong [38]	AI-IoT, smart governance and decision-making	Not central	Not central	Supported	Explicit	Supported	Not central
Miles et al. [39]	IoT-based decision support for atmospheric pollution mitigation	Supported	Not central	Limited	Explicit	Not central	Limited
Ramadan et al. [42]	Federated-learning IoT environmental monitoring (industrial)	Explicit	Not central	Explicit	Limited	Limited	Not central
Asha et al. [25]	IoT-enabled AI air pollution monitoring (environmental toxicology)	Explicit	Not explicit	Explicit	Supported	Not explicit	Limited
Proposed framework	Urban pollution intelligence and sustainable governance	Explicit	Explicit	Explicit	Explicit	Explicit	Explicit

Note: The classifications represent qualitative literature-based mapping rather than performance ratings. *Explicit* indicates direct incorporation into the study's framework or primary scope; *Supported* indicates substantive coverage without being a central architectural component; *Addressed broadly* indicates conceptual treatment without detailed architectural integration; *Limited* indicates partial treatment; *Not central* indicates that the capability lies outside the study's primary scope; and *not explicit* indicates that it is not explicitly represented in the reported architecture.

Table 7. Conceptual Mapping of Case-Study Capabilities to the Proposed Framework

Framework Layer	Capability Reported in Source Study	Conceptual Mapping to Proposed Framework	References
Layer 1: Data Acquisition	Environmental sensing and IoT-based data acquisition	Corresponds to the framework's environmental sensing and data-acquisition functions	[6,25,26,34]
Layer 2: Data Processing and Integration	Environmental data processing and transmission	Maps to data preprocessing, integration, and management functions	[12,25,28,35,36]
Layer 3: AI Analytics	Data-driven environmental analysis/monitoring capabilities	Maps to selected analytical functions; additional forecasting, source attribution, anomaly detection, and XAI capabilities are framework extensions where not reported	[5,9,25,29,30,37]
Layer 4: Intelligent Decision Support	Monitoring outputs supporting environmental management	Conceptually maps to alerts and decision-support functions; broader policy simulation and intervention optimization remain proposed capabilities	[14,25,38,39]
Layer 5: Ethical AI and Governance	Not explicitly reported	Proposed extension incorporating explainability, privacy, fairness, accountability, and stakeholder participation	[24,40,41,42]
Layer 6: Sustainability and SDG Alignment	Not explicitly reported	Proposed extension linking environmental intelligence and governance outcomes to measurable sustainability targets	[43,46,47,48]

Note: The source study [25] did not implement or evaluate the six-layer framework. Layers 5 and 6 are proposed extensions; references cited for them support the extension concepts and are not capabilities reported in the source study.

Scientific Significance and Contribution

The scientific contribution of the proposed framework lies in establishing a unified pathway connecting environmental intelligence with

responsible urban governance and sustainability assessment. Rather than developing new algorithms, it provides an integrated reference architecture that supports the translation of AI-

generated pollution information into actionable decisions and measurable outcomes.

Specifically, the framework addresses three integration challenges: (1) technical-to-analytical integration, linking heterogeneous sensing with pollution analytics; (2) analytical-to-governance integration, enabling explainable and accountable decision support; and (3) governance-to-sustainability integration, connecting interventions with measurable sustainability indicators. These connections provide a multidisciplinary foundation for coordinated environmental monitoring, urban governance, public health, and sustainability planning.

Practical Applicability and Deployment Considerations

The modular architecture allows the framework to be adapted to different urban contexts according to available sensing infrastructure, data, computational resources, and governance capacity. Depending on application requirements, lightweight models and edge computing can support low-latency monitoring, while more computationally intensive models may use cloud or hybrid edge–cloud environments. This flexibility supports applications ranging from localized pollution monitoring to broader city-scale environmental intelligence.

Practical deployment nevertheless involves trade-offs among predictive performance, latency, computational cost, interpretability, scalability, and energy consumption. Implementation may also be constrained by fragmented data systems, limited sensing and computing infrastructure, interoperability challenges, deployment and maintenance costs, regulatory uncertainty, and shortages of technical expertise, particularly in resource-constrained municipalities. These challenges highlight the need for context-specific model selection, interoperable standards, scalable infrastructure, and phased implementation.

Potential applications include pollution forecasting and early warning, hotspot identification, pollution source attribution, policy and intervention assessment, and environmental decision support. However, these represent intended applications of the conceptual framework rather than experimentally demonstrated deployments; their effectiveness requires future implementation and empirical evaluation.

Ethical and Governance Implications

The integration of AI into urban environmental management introduces important concerns related to privacy, security, algorithmic bias, transparency, and accountability. These issues are particularly relevant when

environmental data are combined with mobility, location, or citizen-generated information. Responsible deployment therefore requires privacy-preserving data practices, bias assessment, explainable AI, and appropriate regulatory oversight.

The framework further emphasizes stakeholder participation and institutional accountability to ensure that AI-generated environmental intelligence supports transparent and inclusive decision-making. These mechanisms are important for building trust among government agencies, researchers, industries, and communities while reducing the risk of unequal environmental representation or intervention. Ethical governance should therefore be treated as an integral component of AI-IoT environmental intelligence rather than an additional technical requirement.

Implications for Sustainability and Urban Governance

The framework links environmental intelligence with sustainability-oriented urban governance by translating pollution monitoring, forecasting, and source-attribution outputs into information that can support targeted interventions and policy assessment. This linkage is relevant to SDG 3.9 through pollution-related health protection, SDG 11.6 through improved urban air-quality management, and SDG 13.2 through the integration of environmental intelligence into climate-related planning.

Importantly, SDG alignment in the proposed framework represents a pathway for assessing sustainability outcomes rather than evidence of achieved impacts. Future implementation should therefore define measurable indicators to evaluate whether AI-supported interventions produce environmental, health, and governance improvements. This would enable sustainability objectives to become explicit evaluation criteria rather than broader contextual goals.

Study Limitations and Future Research

This study has several limitations. First, the proposed framework is conceptual and has not been implemented or empirically evaluated as an integrated system. Although literature mapping, comparative framework analysis, and case-study mapping provide theoretical and practical grounding, they do not demonstrate end-to-end operational performance. Second, implementation feasibility may vary across cities because of differences in data availability, sensing infrastructure, computational resources, regulatory environments, and institutional capacity. Finally, the literature synthesis may not

capture all emerging AI-IoT techniques and applications.

Future research should progressively evaluate the framework through expert assessment, scenario-based analysis, prototype development, pilot deployment, and quantitative evaluation. Empirical studies should examine predictive performance, latency, scalability, interoperability, robustness, computational and deployment costs, explainability, stakeholder acceptance, and governance effectiveness across diverse urban environments. Cross-city and cross-regional studies would further assess the framework's adaptability and generalizability.

The roadmap progresses from short-term conceptual refinement and expert evaluation to medium-term prototype development and pilot deployment, followed by long-term cross-city evaluation and broader integration. This staged progression enables technical performance, governance requirements, stakeholder acceptance, and sustainability outcomes to be assessed before large-scale implementation.

Figure 2 presents a staged research and implementation roadmap for progressing from conceptual development toward practical implementation and empirical validation of the proposed framework.

CONCLUSION

This study proposed an integrated AI-IoT conceptual framework for urban pollution source detection and sustainable smart-city governance. The six-layer architecture connects multi-source environmental sensing, data integration, AI-driven pollution intelligence, decision support, responsible AI governance, and sustainability alignment within an end-to-end architecture.

Regarding RQ1, the framework integrates heterogeneous environmental sensing with AI-based forecasting, hotspot and anomaly detection, and pollution source attribution to support urban pollution intelligence. For RQ2, it connects analytical outputs with explainable decision support, stakeholder participation, and responsible AI governance to support transparent and accountable urban decision-making. For RQ3, it links environmental intelligence and governance actions with measurable sustainability objectives, particularly SDG 3.9, SDG 11.6, and SDG 13.2.

The framework was conceptually evaluated through literature mapping, comparative framework analysis, and case-study mapping, providing theoretical, comparative, and application-oriented support for its architecture. However, these approaches do not constitute empirical validation of the integrated system.

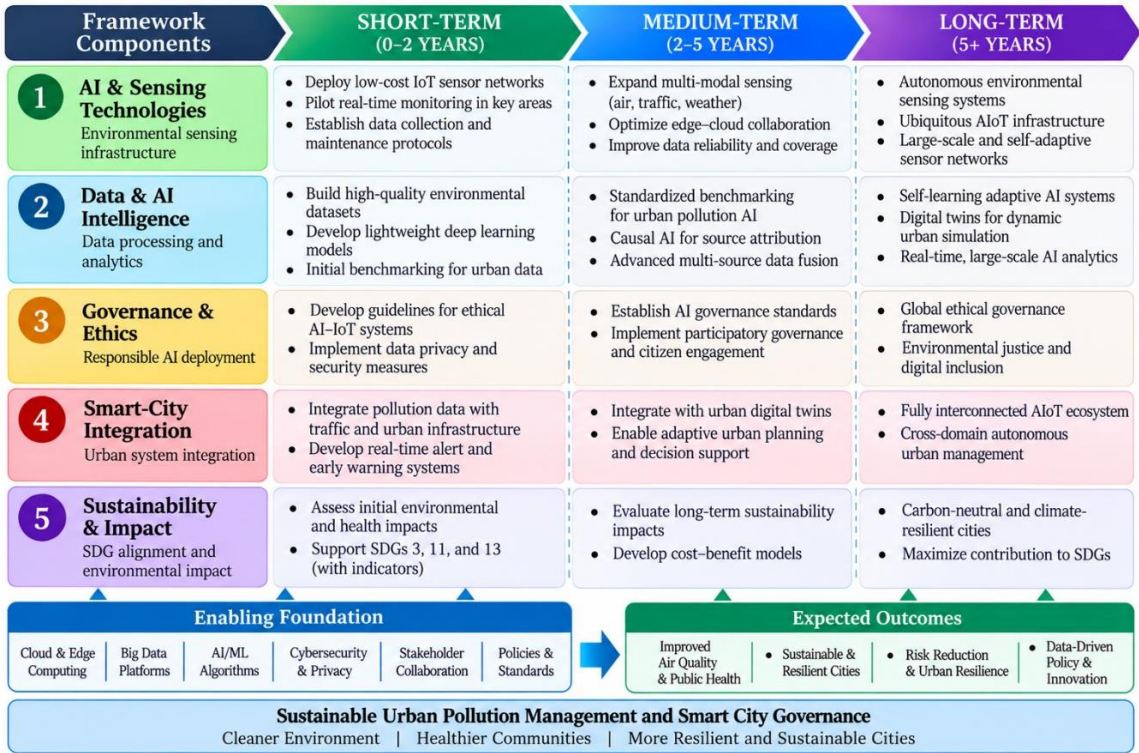


Figure 2. Research and Implementation Roadmap for the Proposed AI-IoT Framework

Future research should therefore focus on prototype development, pilot deployment, quantitative evaluation, and cross-city studies to assess performance, scalability, interoperability, governance effectiveness, and sustainability outcomes. Overall, the framework provides a structured foundation for developing responsible, governance-oriented, and sustainable AI-IoT urban pollution intelligence systems.

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DECLARATION ON GENERATIVE AI

Generative AI tools supported language refinement and manuscript clarity. All scientific content was developed and verified by the authors, who reviewed all AI-assisted content and take full responsibility for the manuscript's accuracy, originality, and integrity.

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