



AI-Driven Smart Cities: A Comprehensive Review of Technologies, Applications, and Future Directions

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ABSTRACT

Artificial intelligence-based monitoring has become an essential technological direction in the development of smart cities, where large-scale sensing, data analytics, and automated decision-support systems are increasingly used to improve urban efficiency, sustainability, safety, and quality of life. As modern cities face growing challenges related to traffic congestion, environmental pollution, energy consumption, public safety, waste management, infrastructure degradation, and rapid population growth, conventional monitoring approaches are no longer sufficient for supporting timely and adaptive urban decision-making. This review examines the role of artificial intelligence in smart-city monitoring by analyzing how machine learning, deep learning, computer vision, Internet of Things sensing, edge computing, and cloud-based analytics contribute to real-time observation, prediction, anomaly detection, and intelligent control across different urban domains. The review highlights major application areas, including traffic-flow monitoring, air-quality prediction, energy management, smart surveillance, waste monitoring, disaster detection, infrastructure inspection, and public-service optimization. It also discusses how artificial intelligence enables cities to move from reactive management toward predictive and preventive governance by identifying hidden patterns in heterogeneous urban data and supporting faster responses to emerging risks. Despite these advantages, the deployment of AI-based monitoring in smart cities remains associated with several challenges, including data privacy, cybersecurity, algorithmic bias, limited interoperability, high infrastructure cost, dependence on reliable sensor networks, and the need for transparent and explainable decision-making. Overall, this review shows that AI-based monitoring can significantly strengthen the operational intelligence of smart cities when it is implemented within ethical, secure, scalable, and citizen-centered governance frameworks.

Keywords: Artificial intelligence; Smart cities; Urban monitoring; Internet of Things; Sustainable urban management.

1. INTRODUCTION

The rapid expansion of urban populations, transportation networks, industrial activities, and high-density infrastructure has intensified the environmental and operational challenges faced by modern cities. Among these challenges, urban noise pollution has become one of the most persistent yet frequently underestimated threats to public health, environmental quality, and urban livability. Unlike visible forms of pollution, noise

is often treated as a temporary inconvenience, although continuous exposure to high sound levels can contribute to sleep disturbance, stress, reduced cognitive performance, hearing-related problems, and broader physiological risks. In the context of smart cities, this issue requires more than conventional measurement; it requires intelligent, scalable, and data-driven monitoring systems capable of transforming acoustic signals and related urban variables into actionable knowledge. Artificial Intelligence (AI) has therefore become a central enabling

technology for smart-city development because it allows urban systems to learn from heterogeneous data, detect complex patterns, and support evidence-based decision-making across dynamic city environments.

Traditional noise monitoring approaches commonly rely on fixed physical sensors or periodic manual measurements. Although these methods can provide useful localized readings, they remain limited in spatial coverage, maintenance cost, scalability, and predictive capability. A fixed sensor can measure the sound level at a specific point, but it cannot easily explain the source of the noise, estimate acoustic conditions in unmonitored areas, or forecast future changes caused by traffic intensity, weather variation, construction activity, or temporal patterns. This limitation creates acoustic blind spots in urban management, where decision-makers may not have sufficient information to identify high-risk zones or design effective mitigation strategies. AI-based monitoring offers a stronger alternative by integrating sensor readings, traffic data, meteorological variables, spatial information, and historical records into predictive models that can estimate, classify, and visualize urban noise conditions more intelligently. This shift reflects the broader movement in smart-city research toward AI-enabled systems that improve prediction, automation, service quality, and urban sustainability [1].

Within this review, AI-based monitoring in smart cities is examined through the lens of intelligent urban noise management. The reviewed direction is motivated by the need to move from reactive monitoring toward proactive acoustic intelligence. In a reactive system, city authorities respond after noise levels have already exceeded safe thresholds or after citizens report disturbance. In contrast, an AI-supported system can forecast noise trends, identify likely hotspots, classify dominant sound sources, and issue early alerts before conditions become harmful. Such a system can support multiple smart-city functions, including real-time noise mapping, noise-source identification, temporal forecasting, heatmap visualization, threshold-based notifications, and policy-oriented decision support. Internet of Things (IoT) infrastructure strengthens this process by enabling distributed sensing, continuous data acquisition, and real-time communication between field devices, edge nodes, cloud platforms, and urban dashboards [2].

The technical foundation of AI-based urban noise monitoring depends on the integration of several computational layers. The sensing layer collects acoustic and environmental information through microphones, sound-level meters, traffic sensors, weather APIs, and other urban data streams. The pre-processing layer improves data quality by handling missing values, filtering noise artifacts, normalizing variables, extracting acoustic features, and aligning temporal or spatial records. The analytical layer applies Machine Learning (ML), deep learning, time-series forecasting, computer vision-assisted visualization, and statistical modeling to classify noise sources, predict decibel levels, and detect abnormal acoustic events. The visualization and decision-support layer then converts model outputs into dashboards, heatmaps, alerts, and reports that can be interpreted by citizens, planners, and municipal authorities. Edge computing can further improve this architecture by processing selected data near the source, reducing latency, limiting bandwidth consumption, and supporting

faster responses in real-time smart-city applications [3].

Despite its potential, AI-based monitoring for smart-city noise management also introduces several technical, ethical, and governance challenges. From a technical perspective, urban soundscapes are highly dynamic because traffic, construction, social activity, weather, building geometry, and unexpected events continuously affect acoustic patterns. Models trained in one city or district may not generalize well to another environment without adaptation. In addition, overlapping sound sources, sensor calibration errors, missing data, and class imbalance can reduce prediction and classification reliability. From an ethical and regulatory perspective, audio-based monitoring must be designed carefully to avoid privacy violations, surveillance misuse, algorithmic bias, and opaque automated decision-making. Therefore, future smart-city monitoring systems should combine predictive accuracy with transparency, cybersecurity, privacy-preserving learning, regulatory compliance, and human-centered governance. These concerns are particularly important because AI in smart cities does not only process data; it increasingly shapes public services, urban planning decisions, and citizen experience [4].

Accordingly, this review aims to provide a structured examination of AI-based monitoring in smart cities, with particular emphasis on urban noise pollution as a representative environmental monitoring problem. The review discusses the conceptual foundations of AI-enabled smart-city monitoring, the role of IoT and data-driven sensing, the use of ML and deep learning for noise prediction and classification, and the importance of visualization tools such as heatmaps and dashboards for translating technical outputs into practical urban intelligence. It also addresses the major limitations that affect real-world deployment, including scalability, computational cost, privacy, data quality, interoperability, and policy integration. By synthesizing these dimensions, the review highlights how AI-based monitoring can support healthier, quieter, and more sustainable smart cities when implemented through robust, explainable, and ethically governed system architectures.

2. LITERATURE REVIEW

Artificial intelligence-based monitoring has become a major research direction in smart-city development because it enables urban systems to move beyond static observation toward adaptive, predictive, and decision-oriented intelligence. Earlier smart-city models relied mainly on connected infrastructure, sensor deployment, and data dashboards, but recent approaches increasingly emphasize the role of intelligent algorithms in interpreting large-scale urban data. In this context, AI-based monitoring can support transportation management, environmental assessment, public safety, infrastructure supervision, and citizen-oriented services. The importance of this direction lies in the ability of AI models to process heterogeneous data streams, identify nonlinear relationships, detect abnormal events, and generate actionable outputs for city authorities and residents. This transformation is especially relevant for urban noise monitoring, where raw acoustic measurements alone are insufficient for understanding the spatial, temporal, and contextual nature of sound pollution. Smart-city monitoring therefore requires an integrated framework

that combines sensing, data preprocessing, prediction, visualization, and decision support rather than treating environmental measurement as an isolated technical process [5].

A central theme in the reviewed literature is the transition from conventional monitoring systems to data-driven urban intelligence. Traditional environmental monitoring usually depends on physical sensors that capture local measurements at specific locations. Although these systems are valuable, their coverage is limited by installation cost, calibration requirements, maintenance needs, and spatial constraints. AI-based virtual sensing provides a complementary approach by estimating environmental conditions through related urban variables such as traffic density, weather conditions, temporal features, land-use characteristics, and historical observations. This is particularly important in noise pollution analysis because sound levels vary according to multiple interacting factors, including vehicle flow, construction activity, wind direction, building geometry, public events, and time of day. By learning from these patterns, AI systems can estimate noise levels in monitored and partially unmonitored areas, reducing the dependence on dense physical sensor networks while still supporting high-resolution environmental awareness.

The literature also shows that smart-city AI systems are increasingly designed as multi-layer architectures. The first layer usually consists of Internet of Things sensors, acoustic devices, traffic counters, meteorological data sources, and other urban data streams. The second layer performs data cleaning, synchronization, normalization, feature extraction, and quality control. The third layer applies ML, deep learning, time-series forecasting, anomaly detection, or hybrid models to convert data into predictions and classifications. The final layer presents system outputs through dashboards, geospatial maps, alerts, and recommendation interfaces. This layered design matches the logic of intelligent noise monitoring systems, where sound data must be collected, processed, interpreted, and translated into practical decisions. In urban noise applications, this means that a system should not only measure decibel values but should also explain what is causing the sound, where the highest exposure zones are located, when future peaks may occur, and what type of response is needed.

In smart-city monitoring research, urban AI is not treated only as a technical tool but also as a socio-technical system that influences planning, governance, public services, and citizen experience. This is important because AI-based monitoring platforms can affect how cities regulate mobility, enforce environmental standards, prioritize infrastructure investment, and communicate risk to the public. For example, real-time noise monitoring can help identify acoustic hotspots near hospitals, schools, residential districts, and traffic corridors. Predictive analytics can support proactive interventions before noise exposure exceeds safe thresholds. Heatmap visualization can make invisible acoustic risk visible to planners and citizens. However, the same monitoring systems may also raise concerns related to privacy, surveillance, transparency, and public acceptance, especially when audio data are collected in public spaces. Therefore, the literature emphasizes that smart-city AI should be designed with technical robustness and human-centered governance together, rather than focusing only on prediction accuracy [6].

Another important contribution in the literature concerns big data analytics and adaptive learning in smart-city environments. Urban systems generate large volumes of dynamic, noisy, incomplete, and heterogeneous data. This creates challenges for conventional AI models that are trained under stable assumptions and fixed data distributions. In the context of AI-based noise monitoring, models may face changing sound patterns caused by new roads, construction projects, seasonal behavior, social events, or changes in transportation policy. Therefore, adaptive models, self-learning pipelines, and continuous updating mechanisms are increasingly important for maintaining performance over time. The ability to handle dynamic data is especially valuable when urban monitoring systems are deployed at scale, because a model trained in one city district may not generalize perfectly to another district with different traffic behavior, building density, or acoustic conditions [7].

Noise-source identification is another major theme connected to AI monitoring in smart cities. Measuring sound intensity is useful, but it does not provide sufficient information for policy action unless the system can determine the dominant source of noise. For instance, traffic noise, construction noise, industrial activity, aircraft noise, emergency sirens, and public-event noise require different mitigation strategies. AI-based sound classification can address this issue by analyzing acoustic fingerprints, spectrograms, MFCCs, and temporal sound patterns. Deep learning models can be trained to distinguish between overlapping urban sounds, while signal processing methods can improve the quality of extracted features before classification. This source-aware approach is critical because urban authorities need to know not only where noise is high but also why it is high. Without source identification, mitigation remains general and reactive; with source classification, interventions can become more targeted, such as traffic rerouting, construction-time regulation, industrial compliance checks, or quiet-zone planning.

Predictive analytics further extends smart-city monitoring from present-state description to future-oriented decision support. In urban noise management, time-series forecasting can be used to estimate future decibel levels based on historical acoustic patterns, traffic behavior, time of day, day of week, meteorological variables, and event-related changes. This makes the system proactive because city authorities can anticipate high-risk periods instead of responding only after noise thresholds are exceeded. Forecasting methods may include statistical models, ML regressors, recurrent neural networks, and hybrid deep learning models, depending on the complexity and availability of the data. The practical value of prediction is evident in applications such as 24-hour noise forecasting, traffic sensitivity analysis, alert preparation, and planning support for construction scheduling or mobility management. In this way, predictive monitoring connects environmental intelligence with operational urban management.

The reviewed literature also highlights the importance of transforming AI outputs into interpretable and usable visual interfaces. Smart-city systems often fail to deliver practical impact when their results remain hidden in technical logs, numerical tables, or model outputs that are difficult for non-specialists to understand. For this reason, heatmaps,

geospatial dashboards, threshold gauges, trend charts, and alert panels are essential components of AI-based monitoring. In urban noise management, heatmap visualization converts acoustic predictions into spatial patterns that can be understood immediately by policymakers and citizens. Red zones can indicate high-exposure areas, while lower-intensity zones can support the identification of quieter urban spaces. These visual tools are not only presentation elements; they are part of the decision-support system because they help stakeholders locate problems, prioritize interventions, and communicate environmental risks.

The connection between AI, IoT, and decision support is also central to smart-city monitoring research. IoT networks provide continuous streams of data, while AI models interpret these streams and convert them into predictions, classifications, or alerts. In a noise-monitoring system, IoT devices may include acoustic sensors, environmental sensors, traffic sensors, and edge gateways. These devices can send data to cloud platforms or process part of the data locally through edge computing. AI-driven decision support can then identify abnormal sound conditions, trigger notifications, update dashboards, or recommend mitigation actions. This architecture supports a shift from isolated sensing devices toward integrated smart-city platforms where data acquisition, analysis, visualization, and response are connected within a single monitoring cycle [8].

However, the deployment of AI-based monitoring systems in real smart cities remains challenging. Technical challenges include noisy data, missing values, sensor drift, class imbalance, model overfitting, computational cost, latency, and limited transferability across locations. Acoustic monitoring adds further complexity because urban soundscapes often contain overlapping sound sources and environmental distortions caused by wind, rain, reflections, and physical barriers. Operational challenges include sensor maintenance, calibration, network reliability, power consumption, and system scalability. Governance challenges include privacy, cybersecurity, regulation, user trust, and the need for transparent model behavior. These challenges demonstrate that AI-based smart-city monitoring cannot be evaluated only according to model accuracy. A successful system must also be reliable, secure, explainable, scalable, and aligned with public-interest governance [9].

Overall, the literature indicates that AI-based monitoring can significantly improve smart-city environmental management when it is implemented as an integrated and human-centered system. For urban noise pollution, the most relevant capabilities include real-time data acquisition, acoustic feature extraction, noise-source classification, temporal forecasting, heatmap visualization, alert generation, and policy-oriented decision support. The uploaded project framework follows this direction by emphasizing virtual sensing, predictive modeling, dashboard-based visualization, and context-aware alerting. Therefore, the present review positions AI-based noise monitoring as a representative case of smart-city intelligence: it demonstrates how AI can transform invisible environmental stressors into measurable, interpretable, and actionable urban knowledge.

This review adopts a narrative and application-oriented methodology to examine AI-based monitoring in smart cities,

with a focused emphasis on urban noise pollution as a representative environmental monitoring problem. The methodological design was selected because the topic combines multiple research domains, including smart cities, AI, IoT, acoustic sensing, predictive analytics, edge computing, environmental monitoring, visualization, and urban governance. Rather than treating these domains separately, the review synthesizes them into a structured discussion that reflects how an intelligent smart-city monitoring system is designed, deployed, and evaluated.

The review process was organized into four stages. First, relevant studies were identified from the provided BibTeX database, with priority given to sources addressing AI in smart cities, IoT-enabled monitoring, urban computing, adaptive analytics, smart-city security, and AI-based decision support. Second, the uploaded UrbanSense AI document was used as the technical reference for defining the thematic structure of the review, particularly the sections related to real-time noise mapping, noise-source identification, predictive analytics, heatmap visualization, alert systems, implementation architecture, challenges, and future directions. Third, the selected literature was grouped according to its contribution to smart-city monitoring: conceptual foundations, sensing and data integration, AI modeling, visualization and decision support, deployment constraints, and governance considerations. Fourth, the synthesized findings were written in a two-column-compatible format suitable for the provided journal class.

Because the manuscript uses a two-column layout, the methodology avoids oversized tables, long equations, and wide figures that may disrupt column flow. If a table is needed later, it should either be compact enough to fit within one column or placed as a full-width floating table using `table*`. For concise methodological summaries inside one column, the following format is preferred: The methodological synthesis presented in Table 1 demonstrates that the remaining studies collectively extend the review beyond general AI-based smart-city monitoring by addressing traffic intelligence, mobile sensing, environmental sustainability, optimization, public acceptance, governance, AI urbanism, and secure data infrastructures. These directions are highly relevant to AI-driven smart-city monitoring because modern urban systems do not operate through a single technology or isolated data stream. Instead, they require a coordinated framework in which sensing devices, intelligent algorithms, visualization tools, policy mechanisms, and citizen-facing services work together to support safer, healthier, and more sustainable cities. In relation to urban noise monitoring, these studies help explain how acoustic intelligence can be connected to traffic systems, environmental planning, public trust, real-time decision support, and secure digital infrastructures.

The first citation focuses on the integration of AI and IoT for traffic congestion reduction. This direction is important because traffic is one of the dominant contributors to urban noise pollution, particularly in dense metropolitan areas where vehicle flow, honking, engine noise, braking, and congestion-related idling create persistent acoustic stress. From a methodological perspective, the first citation supports the idea that AI-based noise monitoring should not depend only on sound sensors. Instead, it should integrate traffic-related variables

Table 1. End-of-section synthesis of remaining studies relevant to AI-based monitoring and smart-city intelligence.

Reference	Research direction	Methodological emphasis	Relevance to AI-based smart-city monitoring	Remaining gap
[10]	AI-enabled IoT for traffic congestion reduction	Examines how AI and IoT can be combined to support traffic monitoring, congestion analysis, and urban mobility improvement.	Relevant to AI-based noise monitoring because traffic is one of the dominant sources of urban noise and must be integrated into acoustic prediction models.	The focus is mainly on congestion reduction, while direct acoustic sensing and sound-level prediction are not deeply addressed.
[11]	AI-based smart-city surveillance using UAVs	Reviews the use of UAV-enabled AI techniques for urban surveillance, monitoring, and data acquisition.	Supports the idea that smart-city monitoring can be expanded through mobile sensing platforms that observe areas not fully covered by fixed sensors.	The UAV-centered approach requires further adaptation for privacy-preserving environmental and acoustic monitoring.
[12]	Environmentally sustainable smart cities	Synthesizes the convergence of AI, IoT, and big data for environmentally sustainable urban development.	Provides strong support for positioning AI-based noise monitoring as part of a broader environmental sustainability framework.	The study is extensive but broad, so noise-specific modeling, acoustic heatmaps, and real-time alert systems require more focused treatment.
[13]	AI-enabled smart-city management using optimization	Uses multi-objective optimization strategies to support intelligent management and decision-making in smart-city environments.	Relevant because AI-based monitoring outputs can support optimization of traffic, environmental control, and resource allocation.	The optimization framework is useful, but direct integration with acoustic sensing and public-health-oriented noise management remains limited.
[14]	Citizen perceptions of AI in smart cities	Investigates how citizens perceive AI-based smart-city systems, including concerns related to monitoring, benefit, risk, and trust.	Important for audio-based smart-city monitoring because public acceptance depends on privacy, transparency, and perceived usefulness.	The study focuses on perception and acceptance, while technical implementation of AI monitoring systems is outside its main scope.
[15]	Systematic literature network analysis of AI in smart cities	Maps research trends and knowledge structures related to AI applications in smart-city studies.	Useful for understanding the broader research landscape in which AI-based environmental and acoustic monitoring is positioned.	The network-analysis perspective is valuable, but it does not provide a detailed technical pipeline for real-time urban noise monitoring.
[16]	AI promises for public organizations and smart cities	Discusses the potential of AI to improve public-sector operations, service delivery, and smart-city governance.	Relevant because AI-based monitoring systems must ultimately support public organizations in planning, regulation, and service improvement.	The discussion is governance-oriented and requires stronger technical connection to sensing, prediction, visualization, and automated alerts.
[17]	AI urbanism and post-smart cities	Critically examines the rise of AI urbanism and its influence on urban governance, planning, autonomy, and city transformation.	Supports a critical perspective on AI monitoring by showing that intelligent systems can reshape urban life and decision-making structures.	The study is mainly conceptual and critical, so practical design methods for ethical acoustic monitoring still need further development.
[18]	AI and blockchain technologies for smart cities	Explores how AI and blockchain can support secure, intelligent, and sustainable smart-city systems.	Relevant because blockchain-like mechanisms may improve trust, traceability, and integrity in distributed smart-city monitoring data.	The relationship between blockchain security and continuous acoustic sensing requires further applied validation.

such as vehicle density, road occupancy, peak-hour patterns, and mobility flow. This connection allows the monitoring system to explain why noise levels increase in specific areas and helps city authorities design more targeted mitigation strategies. However, the main limitation is that the study's focus remains primarily on congestion reduction, while direct acoustic sensing, sound-source classification, and decibel-level prediction require further specialization.

The second citation addresses AI-based smart-city surveillance using unmanned aerial vehicles. This contribution is relevant because it expands the idea of smart-city monitoring beyond fixed sensors and stationary infrastructure. In many cities, fixed monitoring devices cannot cover all districts equally, especially in large urban spaces, temporary construction zones, emergency areas, or locations with limited infrastructure. Mobile sensing platforms can help fill these gaps by collecting information from flexible viewpoints and supporting dynamic environmental observation. For urban noise monitoring, this suggests that future systems may combine fixed acoustic sensors with mobile or aerial sensing platforms to improve spatial coverage. Nevertheless, this direction also raises important concerns regarding privacy, surveillance acceptability, and ethical deployment, particularly when monitoring technologies are used in public spaces.

The third citation contributes to the review by connecting AI, IoT, and big data with environmentally sustainable smart-city development. This perspective is central to the present review because noise pollution is not only a technical monitoring

problem but also an environmental and public-health issue. The third citation supports the argument that AI-based monitoring should be embedded within a broader sustainability framework that also considers air quality, mobility, energy use, urban comfort, and quality of life. In the context of acoustic monitoring, this means that noise heatmaps, prediction models, and alert systems can support healthier urban planning by identifying high-exposure zones and guiding mitigation policies. The limitation is that the study is broad in scope, so noise-specific elements such as acoustic feature extraction, sound-source recognition, real-time threshold alerts, and predictive noise mapping still require focused discussion.

The fourth citation is relevant because it examines AI-enabled smart-city management through optimization. This is important because monitoring alone does not solve urban problems unless the information is converted into improved decisions. For example, once an AI system identifies a noisy district or predicts a future noise peak, optimization methods can help determine the best response, such as rerouting traffic, changing signal timing, adjusting construction schedules, or prioritizing green-buffer interventions. Therefore, the fourth citation supports the transition from passive monitoring to active urban management. Its main limitation is that optimization is not directly connected to acoustic sensing in a detailed way. Future research should therefore explore how optimization models can use predicted noise levels, sound-source categories, and spatial heatmaps as inputs for decision-making.

The fifth citation focuses on citizen perceptions of AI in smart cities. This direction is especially important for audio-based monitoring because public acceptance is essential when technologies collect or process data in shared urban environments. Even when a system is designed for environmental protection, citizens may worry about surveillance, privacy, data misuse, or lack of transparency. The fifth citation therefore strengthens the review by showing that technical performance alone is not enough for successful smart-city deployment. AI-based monitoring systems must also be understandable, trustworthy, and socially acceptable. In urban noise monitoring, this means that systems should avoid storing unnecessary raw audio, explain why data are collected, provide transparent outputs, and communicate benefits clearly to the public. The main gap is that perception-focused research does not usually provide detailed implementation guidance for model design, signal processing, or real-time deployment.

The sixth citation provides a systematic literature network analysis of AI in smart cities. Its value lies in mapping the broader research landscape and showing how AI-related smart-city studies are connected across different domains. This is useful for the present review because AI-based monitoring is an interdisciplinary topic that combines urban analytics, IoT systems, environmental sensing, predictive modeling, governance, and public services. For noise monitoring, such a network perspective helps position acoustic intelligence as part of a wider smart-city research ecosystem rather than a narrow technical application. However, the limitation is that network analysis usually identifies research trends and relationships between studies, but it does not provide a complete technical pipeline for building real-time acoustic monitoring systems.

The seventh citation discusses the promises of AI for public organizations and smart cities. This is relevant because AI-based monitoring systems are ultimately intended to support public-sector decision-making. A smart noise monitoring system may generate predictions, dashboards, alerts, and reports, but these outputs become meaningful only when public organizations can use them for planning, regulation, enforcement, and community protection. The seventh citation therefore supports the governance and institutional dimension of the review. It highlights that AI can improve public-service delivery, but also requires organizational readiness, data governance, technical capacity, and clear decision-making procedures. The remaining gap is that governance-oriented studies often do not explain how sensing, prediction, visualization, and alerting should be technically integrated into a working environmental monitoring platform.

The eighth citation critically examines AI urbanism and post-smart-city development. This contribution is important because it reminds the review that AI-based monitoring should not be discussed only as a positive technological advancement. Intelligent monitoring systems can reshape how cities are governed, how decisions are made, and how citizens experience urban life. In the context of noise monitoring, AI can support public health and environmental planning, but it can also introduce concerns related to automation, surveillance, unequal monitoring, and reduced human oversight. The eighth citation therefore provides a critical balance to the technical discussion. It supports the need for ethical,

transparent, and accountable AI systems, especially when monitoring technologies are deployed across public spaces. Its limitation is that it is mainly conceptual and does not provide detailed practical methods for implementing ethical acoustic monitoring systems.

The ninth citation examines AI and blockchain technologies for smart cities. This is relevant because large-scale monitoring systems depend on distributed data flows, sensor networks, and digital records that must remain secure, traceable, and trustworthy. In AI-based noise monitoring, data may come from multiple sensors, edge devices, cloud platforms, and dashboards. Ensuring that these data are not manipulated, lost, or accessed improperly is essential for reliable decision-making. The ninth citation therefore supports the idea that secure digital infrastructures may strengthen trust in smart-city monitoring systems. However, the direct relationship between blockchain-like mechanisms and continuous acoustic sensing still requires further applied validation, particularly in terms of computational cost, latency, scalability, and integration with real-time AI models.

Overall, the remaining citations summarized in Table 1 expand the methodological foundation of the review by showing that AI-based smart-city monitoring is shaped by technical, environmental, social, institutional, and security-related factors. The first citation connects noise monitoring to traffic intelligence, the second citation expands monitoring through mobile sensing, the third citation situates AI monitoring within environmental sustainability, and the fourth citation links monitoring outputs to optimization-based decision-making. The fifth citation adds the citizen-trust dimension, the sixth citation provides a research-landscape perspective, the seventh citation highlights public-sector relevance, the eighth citation introduces a critical governance lens, and the ninth citation emphasizes secure data infrastructures. Together, these references show that AI-driven smart-city monitoring must be designed as an integrated system that is predictive, scalable, interpretable, privacy-aware, secure, and connected to real urban decision-making.

2.1 AI-Based Urban Monitoring and Data Fusion

AI-based urban monitoring depends on the ability to combine multiple sources of city data into a unified analytical framework. In smart cities, environmental conditions are rarely shaped by a single factor. Noise pollution, for example, is influenced by traffic flow, road structure, building density, industrial activity, public events, weather conditions, and time-dependent human behavior. For this reason, intelligent monitoring systems must move beyond isolated acoustic readings and integrate heterogeneous data streams. These may include decibel measurements, traffic counts, meteorological variables, geospatial coordinates, temporal indicators, and historical environmental records. Through this fusion process, AI models can identify relationships that are difficult to detect through manual inspection or traditional statistical monitoring.

The value of data fusion becomes especially clear in urban noise analysis. A high sound level recorded in a busy street may be caused by traffic congestion, construction activity, emergency vehicles, or temporary public events. Without contextual data, the monitoring system may detect the intensity of

the problem but fail to explain its cause. By integrating acoustic data with traffic and environmental variables, the system can generate more meaningful interpretations. This supports the development of predictive and source-aware monitoring frameworks in which the model does not only estimate sound levels, but also links them to possible urban drivers. Such integration is important for future smart-city platforms because it allows environmental monitoring to become more explanatory, scalable, and useful for decision-making [10].

2.2 Predictive Analytics for Urban Noise Intelligence

Predictive analytics is one of the most important components of AI-based smart-city monitoring because it changes the role of environmental systems from reactive observation to proactive management. Conventional monitoring systems usually report current or past conditions, which means that city authorities often respond after the problem has already occurred. In contrast, predictive models can forecast future conditions by learning from historical patterns, temporal cycles, traffic intensity, and environmental variables. In urban noise monitoring, this capability is particularly valuable because sound exposure often follows predictable rhythms, such as morning and evening traffic peaks, weekend activity patterns, construction schedules, and event-related crowd movement.

In AI-driven noise monitoring, predictive analytics can support short-term and long-term decision-making. Short-term prediction can estimate future decibel levels over the next few hours and trigger early alerts when unsafe exposure is expected. Long-term prediction can help planners identify zones that are likely to experience chronic noise exposure under future traffic or development scenarios. These predictive outputs can support traffic rerouting, construction-time regulation, quiet-zone design, and public-health planning. However, prediction accuracy depends strongly on the quality of input data and the model's ability to generalize across different locations and time periods. Therefore, predictive noise intelligence must be supported by continuous model validation, local calibration, and adaptive updating when urban conditions change [13].

2.3 Visualization, Heatmaps, and Decision Support

Visualization is a critical bridge between AI models and practical smart-city decision-making. Even when an AI system produces accurate predictions, its outputs may remain difficult to use if they are presented only as numerical values, technical logs, or model statistics. Urban planners, policy-makers, and citizens need interpretable representations that show where problems occur, how severe they are, and how they change over time. In this context, heatmaps, dashboards, temporal charts, alert gauges, and geospatial interfaces are essential components of AI-based monitoring systems. They transform abstract analytical outputs into visual evidence that can support planning, communication, and intervention.

For urban noise monitoring, heatmap visualization is especially important because noise pollution is spatially uneven and often invisible to the public. A heatmap can show high-intensity acoustic zones, identify recurring hotspots, and compare exposure levels across different districts. When connected to predictive analytics, heatmaps can also display expected future noise conditions rather than only current mea-

surements. This allows smart-city authorities to prioritize mitigation strategies such as sound barriers, traffic management, green-buffer planning, or zoning adjustments. Visualization therefore should not be treated as a decorative component; it is part of the decision-support system because it determines whether AI outputs can be understood and acted upon by real users.

2.4 IoT, Edge Computing, and Real-Time Deployment

The deployment of AI-based monitoring systems depends heavily on IoT infrastructure and edge computing. IoT devices provide the sensing layer through distributed acoustic sensors, environmental sensors, traffic counters, cameras, and communication modules. These devices allow cities to collect data continuously from multiple locations, creating the foundation for real-time monitoring. However, when monitoring systems operate at city scale, data transmission, storage, latency, and energy consumption become major challenges. This is particularly important for audio-based monitoring because raw audio streams can be large, privacy-sensitive, and expensive to transmit continuously.

Edge computing provides a practical solution by allowing part of the processing to occur near the data source. Instead of sending all raw audio to a central cloud platform, an edge device can extract features, classify sound events, estimate decibel levels, or detect threshold violations locally. This reduces bandwidth consumption, improves response speed, and limits unnecessary exposure of raw acoustic data. In smart-city noise monitoring, edge deployment can support faster alerts, more efficient sensor networks, and better privacy protection. Nevertheless, edge-based systems must balance model complexity with hardware limitations. Lightweight AI models, efficient feature extraction, model compression, and low-power communication protocols are therefore important for practical real-time deployment [3].

2.5 Privacy, Trust, and Governance in AI-Based Monitoring

Privacy and governance are central issues in AI-based smart-city monitoring because intelligent systems often collect data from public spaces and influence public decision-making. In the case of urban noise monitoring, the challenge is particularly sensitive because acoustic sensors may capture human voices or private conversations if raw audio is stored or transmitted without protection. Even when the system is designed only for environmental purposes, citizens may still perceive audio monitoring as a form of surveillance. Therefore, privacy-aware design must be included from the beginning of system development rather than treated as an additional feature after deployment.

A trustworthy AI-based monitoring system should minimize the collection of raw personal data, process information locally where possible, anonymize sensitive signals, and communicate clearly how data are used. Governance is also necessary because AI outputs may support regulatory actions, public alerts, or planning decisions. If the model is biased, inaccurate, or opaque, it may lead to poor interventions or reduce public confidence in smart-city technologies. Therefore, explainability, accountability, cybersecurity, public communication, and human oversight are essential requirements for responsible deployment. Citizen acceptance is especially

important because smart-city monitoring systems are more likely to succeed when residents understand their benefits and trust that their privacy and rights are protected [14].

3. AI-DRIVEN SMART CITY NOISE MONITORING SYSTEM ARCHITECTURE

Figure 1 presents the proposed system architecture for AI-driven smart city noise monitoring. The architecture is designed as an integrated end-to-end pipeline that begins with heterogeneous urban data sources and ends with actionable monitoring services for city planners, environmental authorities, citizens, researchers, and policy makers. The purpose of this architecture is to show that intelligent urban noise monitoring is not limited to measuring sound intensity through acoustic sensors. Instead, it requires a coordinated framework that combines sensing, preprocessing, feature extraction, artificial intelligence analytics, storage, deployment, visualization, alerting, and decision support. This layered design reflects the practical requirements of smart-city systems, where raw data must be transformed into interpretable and useful information before it can support real urban management.

The first layer of the proposed architecture is the data-source layer. This layer includes IoT acoustic sensors, MEMS microphones, traffic data, weather data, GPS or geospatial data, historical urban records, and optional citizen reports or dashboard inputs. Acoustic sensors and microphones provide the direct measurement foundation for urban noise monitoring by capturing sound intensity and acoustic patterns from the physical environment. However, acoustic data alone are not sufficient for intelligent interpretation because urban sound levels are strongly influenced by contextual factors. Traffic data provide information about vehicle density, congestion intensity, road activity, and mobility patterns, which are essential because road transportation is one of the most common sources of urban noise. Weather data, including temperature, humidity, and wind speed, are also necessary because atmospheric conditions influence sound propagation and may affect the relationship between measured and perceived noise. Geospatial data connect each observation to a physical location, enabling the production of maps and spatial hotspot analyses. Historical urban data help the system learn long-term patterns, while citizen reports can provide human-centered feedback about perceived noise discomfort or location-specific disturbances.

The second layer is the data ingestion and preprocessing layer. This layer is responsible for converting raw and heterogeneous inputs into reliable machine-readable data. Data collection and synchronization are necessary because different sources may operate at different sampling rates, spatial resolutions, and temporal intervals. For example, acoustic sensors may produce frequent measurements, traffic systems may update at different intervals, and weather data may be recorded periodically. Without synchronization, the AI model may learn from misaligned observations and produce unreliable predictions. Noise filtering and outlier removal are also essential because real urban data often contain sensor errors, short-term spikes, missing values, or abnormal readings caused by non-representative events. Feature scaling and normalization ensure that variables with different numerical ranges can be processed fairly by machine learning and deep learning models. Acoustic feature extraction then trans-

forms raw sound signals into meaningful descriptors such as MFCC, Log-Mel spectrograms, and spectral features. These features help the model distinguish between different acoustic patterns and support sound classification, noise prediction, and anomaly detection. Finally, temporal and spatial alignment ensures that the system can interpret how noise changes across both time and location.

The third and central layer is the AI analytics engine. This component represents the main intelligence of the proposed monitoring framework. It includes sound classification, noise-level prediction, time-series forecasting, anomaly detection, data fusion, and context awareness. Sound classification allows the system to identify the dominant source or category of noise, such as traffic, construction, industrial activity, social noise, or emergency-related sound. This function is important because decibel levels alone cannot explain the cause of acoustic pollution. Noise-level prediction estimates the expected sound intensity using regression or neural models such as MLP-based prediction. This enables the system to estimate acoustic conditions in monitored and partially unmonitored areas by learning from environmental, mobility, and historical patterns. Time-series forecasting extends this capability by predicting future noise levels over short-term or longer-term horizons. This supports proactive urban management because authorities can anticipate high-noise periods before they occur. Anomaly detection identifies unusual acoustic events or sudden deviations from normal urban patterns, which may indicate emergencies, accidents, illegal construction activity, or unexpected disturbances. Data fusion and context awareness combine acoustic, traffic, environmental, spatial, and temporal information so that the model can interpret noise conditions according to their surrounding urban context.

The fourth layer is the storage and deployment layer. This layer connects the AI engine to the operational infrastructure required for real-world smart-city deployment. Edge processing enables part of the computation to occur close to the sensors or local gateways. This is particularly important in audio-based monitoring because raw acoustic data can be large, privacy-sensitive, and costly to transmit continuously. By extracting features or generating preliminary predictions locally, edge processing reduces latency, bandwidth use, and unnecessary exposure of raw audio. The cloud database or data lake stores processed measurements, historical records, prediction outputs, and monitoring logs. This allows long-term analysis, model evaluation, and policy reporting. The API and model-serving component makes the trained AI models available to dashboards, alert systems, external applications, and decision-support interfaces. Continuous model update and retraining are included because smart-city environments change over time. New roads, construction projects, population movement, traffic regulations, seasonal changes, and urban development can alter the relationship between inputs and noise levels. Therefore, the architecture includes a feedback loop in which monitoring outputs and new data can be used to improve future model performance.

The fifth layer consists of monitoring outputs and services. These outputs are the practical interface between the technical AI system and real urban decision-making. The real-time noise heatmap converts predictions and measurements into spatial visualizations that show where noise intensity is

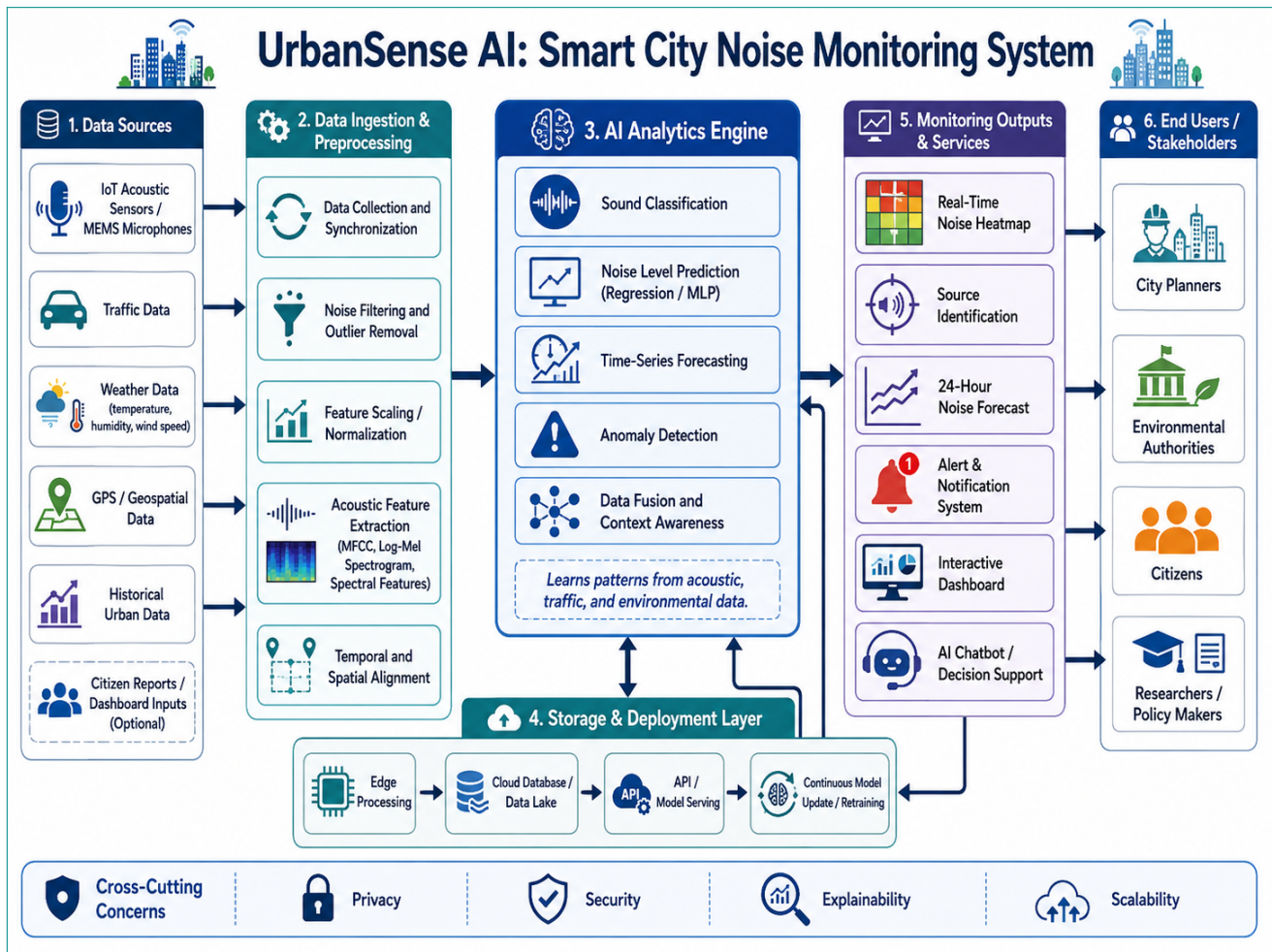


Figure 1. System architecture of the proposed AI-driven smart city noise monitoring framework.

concentrated. This is important because noise pollution is invisible and difficult to communicate through raw numbers alone. A heatmap allows planners and citizens to immediately identify acoustic hotspots and compare noise exposure across districts. Source identification provides more specific information about the likely cause of noise, enabling more targeted mitigation. For example, traffic-related noise requires different interventions from construction-related or industrial noise. The 24-hour noise forecast supports proactive planning by showing expected changes in sound levels across time. The alert and notification system provides automatic warnings when predicted or measured noise exceeds safe or legal thresholds. The interactive dashboard allows users to explore data, maps, trends, and model outputs, while the AI chatbot or decision-support module helps users interpret results through a more accessible interface. Together, these services transform the system from a technical monitoring pipeline into a practical smart-city management tool.

The sixth layer represents the end users and stakeholders who benefit from the monitoring system. City planners can use the outputs to support zoning decisions, traffic redesign, quiet-zone planning, and infrastructure improvements. Environmental authorities can use the system to monitor compliance, identify high-risk areas, and support environmental regulation. Citizens can benefit from accessible information about local noise exposure, safer routes, and environmental quality. Researchers and policy makers can use the collected data and analytical outputs to study urban soundscapes, evaluate

interventions, and design evidence-based regulations. This stakeholder layer is important because AI-based smart-city monitoring is not successful only when the model performs well; it becomes successful when its outputs are understandable, trusted, and useful for real decision-making.

The bottom layer of Figure 1 highlights the cross-cutting concerns that must be considered across the entire system. Privacy is essential because acoustic monitoring may involve sensitive audio data if raw signals are captured or stored without protection. Therefore, the system should minimize raw audio transmission, process features locally where possible, and apply privacy-preserving mechanisms. Security is equally important because distributed sensors, cloud platforms, APIs, and dashboards may be exposed to cyberattacks or data manipulation. Explainability is necessary because stakeholders need to understand why a model generated a warning, prediction, or classification. Without explainability, AI outputs may be difficult to trust or justify in policy contexts. Scalability is also a major concern because a system that works in a small pilot area may not automatically operate effectively across an entire city. Large-scale deployment requires efficient communication, robust infrastructure, model generalization, maintenance planning, and continuous performance monitoring.

Overall, the architecture shown in Figure 1 demonstrates how AI-driven smart city noise monitoring can be implemented as a complete cyber-physical intelligence system. The framework begins with diverse urban data streams, processes them

through a structured preprocessing pipeline, analyzes them using AI models, stores and deploys them through edge-cloud infrastructure, and presents the results through actionable monitoring services. Its main strength lies in connecting prediction with decision support. Rather than only measuring current noise levels, the proposed framework can classify sources, forecast future conditions, detect anomalies, generate alerts, visualize hotspots, and support policy-oriented interventions. This makes the system suitable for smart-city environments that require real-time awareness, proactive planning, and citizen-centered environmental management.

3.1 Security and Integrity of Smart-City Monitoring Data

Security is another important dimension of AI-based monitoring because smart-city systems rely on distributed data flows between sensors, networks, edge devices, cloud platforms, dashboards, and decision-support systems. If these data streams are manipulated, interrupted, or accessed by unauthorized parties, the reliability of the monitoring system can be compromised. In urban noise monitoring, inaccurate or manipulated data could lead to false alerts, incorrect hotspot identification, weak policy decisions, or reduced public trust. Therefore, smart-city monitoring platforms must include secure communication, authentication, access control, encryption, and reliable data-management procedures.

Secure data infrastructure is also important because AI models depend on the quality and integrity of the data used for training and inference. If sensor data are incomplete, corrupted, or intentionally altered, model outputs may become unreliable. Emerging approaches such as blockchain-inspired traceability, secure distributed ledgers, and auditable data pipelines may support stronger trust in smart-city monitoring records. However, these methods must be carefully evaluated because they can introduce additional computational cost and latency. For real-time AI-based noise monitoring, the main challenge is to maintain security without reducing responsiveness or scalability [18].

4. DISCUSSION

The reviewed literature and the methodological synthesis presented in Table 1 show that AI-driven smart-city monitoring is best understood as an integrated intelligence framework rather than a single technological application. The central finding emerging from the review is that smart-city monitoring has gradually shifted from static sensing and descriptive reporting toward predictive, adaptive, and decision-oriented systems. This transition is especially important in urban noise monitoring because acoustic pollution is highly dynamic, spatially uneven, and strongly affected by traffic flow, construction activity, industrial operations, weather conditions, land-use patterns, and human behavior. Conventional monitoring systems can measure sound intensity at fixed points, but they are limited in their ability to interpret causes, forecast future exposure, identify unmonitored hotspots, or recommend timely mitigation actions. Therefore, AI provides an essential analytical layer that transforms raw urban data into usable intelligence for planning, governance, and public-health protection.

A major implication of the reviewed studies is that AI-based monitoring systems must combine multiple data sources to

capture the complexity of real urban environments. Noise pollution cannot be fully understood through acoustic readings alone because sound levels are often the result of interacting environmental and mobility-related factors. Traffic congestion, vehicle speed, wind direction, humidity, temperature, building density, and temporal patterns can all influence the propagation and intensity of urban sound. This supports the need for multimodal monitoring frameworks that integrate acoustic sensing with traffic data, meteorological information, geospatial records, and historical urban activity patterns. Such integration allows AI models to move beyond simple threshold detection and toward contextual interpretation. For example, a high noise level near a hospital at night has different planning implications from a similar level near a commercial area during daytime activity. Context-aware intelligence is therefore essential for reducing false alarms and improving the practical value of monitoring outputs.

The review also highlights the importance of predictive analytics in smart-city monitoring. Traditional monitoring systems are usually reactive because they identify a problem only after it occurs. In contrast, AI-based prediction enables cities to anticipate future noise peaks and prepare mitigation strategies in advance. This capability is significant for urban planning because predicted noise levels can support traffic rerouting, construction scheduling, event management, and the design of quiet zones around sensitive areas such as schools, hospitals, and residential districts. Predictive noise monitoring therefore changes the role of environmental data from passive documentation to proactive decision support. However, this advantage depends heavily on the quality and representativeness of the training data. If datasets are incomplete, biased toward specific locations, or collected under limited conditions, the predictive model may fail when applied to new districts, seasons, or cities. This makes model validation, continuous updating, and cross-environment testing essential requirements for reliable deployment.

Another important discussion point is the role of visualization in transforming AI outputs into practical urban knowledge. Smart-city systems often generate complex technical outputs that may not be immediately useful for policymakers, citizens, or non-specialist users. Heatmaps, dashboards, alert panels, and temporal trend graphs solve this problem by converting numerical predictions into interpretable visual forms. In urban noise monitoring, heatmaps make acoustic risk visible by showing where sound levels are concentrated and how they change across space and time. This visual interpretation supports evidence-based planning because authorities can identify priority zones, compare exposure patterns, and communicate environmental risks more clearly. Visualization also strengthens public awareness by allowing citizens to understand the acoustic quality of their surroundings. Therefore, the success of AI-based monitoring should not be measured only by model accuracy, but also by the clarity, accessibility, and actionability of its outputs.

The reviewed studies further indicate that IoT and edge computing are critical for scalable AI-based monitoring. IoT networks provide the sensing infrastructure needed for continuous data collection, while edge computing allows selected processing tasks to occur near the data source. This is particularly valuable for audio-based monitoring because transmit-

ting raw acoustic data continuously to the cloud may create bandwidth, latency, cost, and privacy challenges. By processing audio features locally, edge devices can reduce communication load and transmit only extracted indicators, predicted noise levels, or classified sound categories. This approach supports faster response times and reduces unnecessary exposure of raw audio data. Nevertheless, edge deployment also introduces constraints related to limited processing power, battery life, hardware cost, and model compression. Future systems must therefore balance computational accuracy with deployment efficiency, especially when operating across large urban areas.

Privacy and governance represent some of the most critical challenges in AI-based smart-city monitoring. Audio-based systems are particularly sensitive because they may capture human voices or other personal information if not designed carefully. Even when the goal is environmental protection, citizens may perceive acoustic monitoring as surveillance unless clear safeguards are implemented. For this reason, responsible AI-based monitoring should prioritize privacy-preserving processing, transparent data policies, anonymization, federated learning where appropriate, and clear communication with the public. Governance is also important because AI-generated predictions can influence policy decisions, enforcement actions, and urban planning priorities. If models are opaque, biased, or poorly validated, they may lead to unfair or ineffective decisions. Therefore, explainability, accountability, cybersecurity, and human oversight must be treated as core design requirements rather than optional additions.

The discussion also reveals that the real-world deployment of AI-based monitoring systems faces significant operational limitations. Sensor drift, hardware degradation, calibration errors, missing data, network instability, environmental noise distortion, and class imbalance can all reduce system reliability. In acoustic monitoring, the problem is intensified by overlapping sound sources, reverberation, weather interference, and differences between urban districts. A model trained on one city's soundscape may not perform well in another city with different traffic culture, road materials, building geometry, or social activity patterns. This limitation demonstrates the need for adaptive learning, local calibration, transfer learning, and continuous performance monitoring. Robustness must therefore become a central evaluation criterion. A smart-city monitoring system should not only perform well during controlled testing, but should remain stable under noisy, incomplete, and changing real-world conditions.

Another major implication is that AI-based monitoring must be connected to actionable decision-making. A system that predicts noise levels or classifies sound sources has limited value if its outputs are not linked to planning, policy, or operational responses. For example, if a model identifies traffic as the dominant source of noise in a residential corridor, the system should support possible interventions such as speed regulation, traffic-light optimization, road-surface improvement, sound barriers, or green-buffer planning. Similarly, if construction noise exceeds acceptable limits during restricted hours, the monitoring platform should provide evidence for regulatory action. This means that AI-based smart-city monitoring should be designed as a decision-support ecosystem, not only as a prediction engine. The integration of alerts,

recommendations, reporting tools, and policy dashboards is therefore essential for practical impact.

Overall, the discussion confirms that AI-driven monitoring can substantially improve smart-city management when it is implemented as a secure, interpretable, scalable, and human-centered system. The strongest potential lies in combining real-time sensing, predictive modeling, acoustic classification, geospatial visualization, alert generation, and governance-aware decision support. At the same time, several limitations must be addressed before large-scale deployment becomes fully reliable. These include data quality, privacy, cross-city generalization, sensor maintenance, computational efficiency, public trust, and institutional readiness. Consequently, future research should move beyond isolated model development and focus on complete monitoring ecosystems that connect sensing, analysis, visualization, decision-making, and ethical governance.

5. CONCLUSION

This review examined AI-driven smart-city monitoring with a particular focus on urban noise pollution as a representative environmental monitoring challenge. The review showed that AI has become an essential component of modern smart-city systems because it enables cities to process heterogeneous urban data, detect hidden patterns, predict future conditions, classify events, visualize risks, and support timely decision-making. In the context of noise pollution, AI-based monitoring offers a strong alternative to conventional approaches that depend mainly on fixed sensors and manual interpretation. By integrating acoustic data with traffic, weather, temporal, and spatial information, AI systems can provide a more complete understanding of urban soundscapes and support more proactive environmental management.

The main conclusion of the review is that AI-based noise monitoring should be designed as an integrated framework rather than a standalone prediction model. Effective systems require coordinated interaction between IoT sensing, data preprocessing, feature extraction, ML and deep learning models, edge or cloud processing, visualization dashboards, alert mechanisms, and policy-oriented decision support. This integrated structure allows smart cities to move from reactive monitoring toward predictive and preventive governance. Instead of simply reporting that noise levels are high, an intelligent system can identify where the problem is occurring, when it is likely to increase, what source may be responsible, which populations may be affected, and what interventions may be suitable.

The review also emphasized that technical performance alone is not sufficient for successful smart-city deployment. While prediction accuracy, classification reliability, and real-time responsiveness are important, they must be supported by privacy protection, cybersecurity, explainability, public trust, and institutional readiness. This is especially important for audio-based monitoring because acoustic data can raise sensitive ethical concerns if raw signals are stored or processed without safeguards. Therefore, future AI-driven monitoring systems should incorporate privacy-preserving methods, transparent model behavior, secure data transmission, and clear governance frameworks. These elements are necessary to ensure that smart-city technologies improve public well-

being without creating new risks related to surveillance, bias, or misuse.

Several research directions can strengthen future work in this field. First, future studies should develop adaptive and self-updating models that can maintain performance as urban environments change. Second, multimodal monitoring should be expanded by combining noise data with air quality, traffic, weather, land use, and population-density indicators. Third, edge computing and lightweight AI models should be further explored to reduce latency, bandwidth consumption, and privacy risks. Fourth, digital twins can be integrated with noise prediction systems to simulate acoustic propagation and test urban planning scenarios before implementation. Fifth, citizen-centered design should be prioritized so that monitoring systems provide understandable information, useful alerts, and transparent explanations to the public. Finally, stronger links between AI outputs and policy mechanisms are needed to ensure that predictions and visualizations lead to practical urban improvements.

In conclusion, AI-driven smart-city monitoring has strong potential to support healthier, quieter, safer, and more sustainable urban environments. For urban noise pollution, AI can transform an invisible and often neglected environmental stressor into measurable, predictable, and actionable intelligence. However, realizing this potential requires more than advanced algorithms. It requires reliable sensing infrastructure, high-quality data, robust models, interpretable visualization, ethical governance, and effective integration with urban decision-making. When these requirements are addressed, AI-based monitoring can become a foundational component of future smart cities and a powerful tool for improving quality of life in increasingly complex urban environments.

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