

Wearable and IoT-Based Monitoring of Indoor Air Pollutants for Personalized Environmental Exposure Assessment

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Abstract

Wearable and Internet of Things based devices are transforming the assessment of personal exposure to indoor air pollutants. Conventional monitoring relies on stationary regulatory networks and occasional personal samplers, which do not capture the microenvironments where most exposure occurs. This paper presents a systems level analysis of wearable and Internet of Things based indoor air quality monitoring, focusing on architectural design, sensor capabilities, data integration, deployment constraints, robustness, fairness, governance, and policy implications. It argues that personalized exposure assessment is not merely a measurement problem but a socio-technical challenge requiring careful alignment of sensing hardware, wireless infrastructure, contextual inference, calibration, and data protection. The discussion reviews exposure assessment and sensor literature, then examines layered architectures comprising wearable nodes, local gateways, edge processing, and cloud based data services. It discusses pollutant sensing technologies and their limitations under realistic indoor conditions, including drift, cross sensitivity, power constraints, and body placement effects. The paper addresses contextual data fusion and exposure modeling, emphasizing uncertainty characterization and interoperability. Deployment considerations include building materials, ventilation, and participatory sensing. Robustness and data quality assurance are framed as continuous processes. The paper further analyzes privacy, fairness, and governance, highlighting the risk that monitoring technologies reproduce unequal exposure burdens while generating sensitive personal data. It concludes with policy and research directions for sustainable, equitable deployment of wearable and Internet of Things based environmental exposure infrastructures.

Keywords

wearable sensing; Internet of Things; indoor air quality; exposure assessment; environmental governance; low-cost sensors.

1. Introduction

In high income and many middle income societies, people spend approximately eighty to ninety percent of their time indoors across residences, workplaces, schools, and transport microenvironments [1]. This time activity pattern means that personal exposure to airborne pollutants is frequently dominated by indoor sources, including combustion for cooking and heating, emissions from building materials and furnishings, consumer products, biological agents, and the indoor penetration of outdoor pollution [2]. Recent advances in low-cost sensing have created opportunities to monitor these pollutants at much higher spatial and temporal resolution than was previously feasible with reference grade monitoring stations [3]. This shift matters for public health because updated international guidelines recognize that fine particulate matter, nitrogen dioxide, ozone, and carbon monoxide can cause adverse health effects at concentrations commonly encountered indoors and outdoors [4]. Extensive epidemiological research has also linked particulate matter exposure to cardiovascular events, reinforcing the need for exposure metrics that reflect where individuals actually spend time rather than relying solely on ambient background concentrations [5].

However, the translation of low-cost sensors into reliable personalized exposure assessment remains difficult. Wearable devices can be carried or worn near the breathing zone, and Internet of Things enabled indoor monitors can be distributed throughout buildings, but their but their measurements are frequently influenced by sensor drift, environmental conditions, placement effects, and calibration drift, which complicates the production of actionable exposure information. The promise of these systems therefore depends not only on the number of devices deployed but on the capacity to integrate heterogeneous data streams into robust, interpretable, and privacy preserving exposure estimates. Low-cost sensor validation remains a persistent challenge across many application domains [6]. This analysis adopts a systems perspective that links hardware selection, network design, data management, and governance to the broader goal of reducing exposure related health disparities. The remainder of the paper examines architectural configurations, sensing limitations, contextual inference, deployment constraints, data quality assurance, fairness, privacy, and policy pathways for wearable and IoT based indoor air pollutant monitoring.

2. System Architecture for Wearable and IoT Based Exposure Monitoring

A layered architecture is common in contemporary wearable and IoT based environmental monitoring systems. At the lowest layer, wearable nodes and stationary environmental sensors acquire pollutant concentration signals, temperature, humidity, and motion data. These devices communicate through short range protocols such as Bluetooth Low Energy, Zigbee, or Wi-Fi to local gateways, which may be smartphones, single board computers, or dedicated home hubs. The gateway layer performs preliminary aggregation, synchronization, and sometimes edge based quality checks before forwarding data to cloud or fog computing resources. Higher layers support long term storage, model training, exposure visualization, and application programming interfaces for external services. This architectural separation permits scalable deployments across multiple buildings and individuals, but it also introduces important trade-offs regarding latency, energy consumption, data loss, and processing complexity [7].

Wearable monitors differ fundamentally from stationary indoor nodes in their power and communication constraints. Because wearables are battery operated and expected to function over many hours without user intervention, their sensing and transmission duty cycles must be carefully managed. Frequent wireless transmission shortens battery life, whereas

infrequent transmission increases latency and may reduce the temporal resolution needed to detect short-lived indoor pollution episodes. Many wearable platforms therefore adopt a hybrid strategy in which raw sensor readings are buffered locally and then transmitted in batches when the device is near a gateway or connected to a smartphone. This design may create gaps in real time visibility but improves energy efficiency and reduces dependence on continuous network connectivity. The choice between edge processing and cloud processing further shapes system behavior. Edge processing can reduce communication overhead and protect privacy by limiting the transfer of raw data, but it may also constrain the complexity of exposure models that can be executed locally.

Architectural decisions are also shaped by the need for contextual information. A pollutant measurement is only meaningful for exposure assessment when it can be associated with an individual, a location, and an activity context. Wearable systems therefore increasingly integrate accelerometers, gyroscopes, and proximity sensors to infer whether a person is sleeping, cooking, commuting, or engaging in physical activity. Indoor IoT networks may incorporate occupancy sensors, window state detectors, and ventilation system feedback. The fusion of these data streams requires middleware that can align timestamps, manage missing values, and reconcile differing sampling rates. Without careful architectural planning, heterogeneous sensing modalities can produce fragmented data silos that are difficult to combine into a coherent exposure history [8].

Another architectural consideration concerns interoperability and data standards. Commercial platforms often use proprietary data formats and cloud interfaces, which can hinder the comparison of exposure estimates across studies and populations. Open architectures that support standardized application programming interfaces and common data models can improve reproducibility and enable the integration of sensor data from multiple vendors. Several research initiatives have proposed data exchange schemas for air quality measurements, but adoption remains uneven across consumer devices and regulatory systems. The absence of harmonized standards increases the burden on data scientists and exposure scientists who must preprocess and validate each new data source. From a systems standpoint, interoperability should be treated as a first class design requirement rather than an afterthought.

3. Sensing Technologies and Calibration Challenges

The sensing layer of wearable and IoT based indoor air pollutant monitoring systems encompasses a wide range of technologies. Optical particle counters and nephelometers are commonly used to estimate particulate matter mass concentrations. Electrochemical sensors are frequently deployed for gases such as carbon monoxide, nitrogen dioxide, and ozone. Metal oxide semiconductor sensors have been applied to detect volatile organic compounds and carbon dioxide equivalents, while photoionization detectors offer selective response for certain organic vapors. These technologies are attractive because of their low cost, small size, and low power consumption compared with reference grade instruments. However, their outputs are influenced by temperature, relative humidity, interfering gases, and sensor aging. Without appropriate correction, readings can drift significantly over time and produce misleading exposure estimates [9].

Calibration is a central challenge for low-cost sensors. Laboratory calibration under controlled conditions is useful for establishing baseline response functions, but field conditions rarely match laboratory settings. Relative humidity can cause hygroscopic particulate matter to absorb water and change its optical properties, producing artifacts in optical particle counters.

Electrochemical sensors may exhibit cross sensitivity to other gases, and their baseline currents can shift with temperature. Metal oxide sensors require periodic heating cycles and may have long response and recovery times. Field colocation with reference instruments is widely regarded as a best practice for deriving correction models, yet colocation opportunities are often limited indoors. Indoor microenvironments vary in ventilation rate, source strength, and occupancy, so correction models developed in one home or office may not transfer reliably to another [10].

Sensor placement on the body introduces additional variability. A wearable monitor clipped to a collar or backpack may be affected by localized sources such as cooking fumes or personal care products, while a wrist worn device may not capture breathing zone concentrations as accurately. The physics of indoor air mixing means that pollutant concentrations can vary substantially over short distances, especially near emission sources. As a result, a single wearable sensor cannot fully represent the spatial heterogeneity of an indoor environment. Some systems address this limitation by deploying multiple stationary nodes in combination with one or more wearable devices, using the stationary network to estimate spatial gradients and the wearable to track personal mobility. This hybrid approach increases complexity but can improve exposure assignment when aligned with time activity data [11].

Data quality assurance for low-cost sensors involves more than one-time calibration. Continuous validation strategies include periodic colocation, drift detection through zero air or span gas checks, and machine learning based anomaly detection. The use of redundant sensors and cross validation between wearable and stationary nodes can also identify erroneous readings. However, these approaches require stable reference materials and maintenance workflows that may be difficult to sustain in long term community deployments. The trade-off between cost and accuracy is therefore not simply a technical parameter but a design constraint that affects the credibility of exposure estimates and their acceptance by public health agencies [12].

4. Contextual Data Fusion and Exposure Modeling

Exposure assessment traditionally relies on estimates that combine ambient concentrations, building characteristics, and time activity patterns. Wearable and IoT based systems offer the possibility of direct personal monitoring, but the resulting data are noisy and incomplete. Contextual data fusion aims to reduce uncertainty by integrating pollutant concentrations with information about location, activity, building ventilation, and source events. For example, a rapid increase in carbon monoxide and particulate matter during evening hours can be associated with cooking activity if stove use data or thermal sensor signals are available. Similarly, a decrease in indoor pollutant levels can be linked to window opening or mechanical ventilation operation. These contextual inferences improve exposure reconstruction by distinguishing true exposure events from sensor artifacts [13].

Spatiotemporal exposure models can take several forms. Deterministic mass balance models estimate indoor concentrations from outdoor concentrations, emission rates, and air exchange rates. Statistical models use regression or machine learning to predict personal exposure from sensor signals and contextual features. Hybrid models combine mechanistic constraints with data driven learning to improve generalization. The choice of modeling strategy is influenced by the available data infrastructure and the intended application. For population scale exposure surveillance, computationally efficient models that can process large volumes of streaming data are necessary. For individual level health studies, models that preserve

interpretability and quantify uncertainty may be preferred over black box predictive models. Both approaches require careful handling of missing data and temporal misalignment [14].

Uncertainty characterization is essential for personalized exposure assessment. A wearable sensor may report a particulate matter concentration with a known measurement error, but this error propagates through exposure averaging and health risk estimation. When contextual variables are integrated, additional uncertainty arises from activity classification errors, indoor source attribution, and ventilation rate estimates. Probabilistic frameworks can represent these uncertainties and provide confidence intervals around exposure estimates. However, many current commercial systems present a single numerical value without accompanying uncertainty information, which risks overinterpretation by users. From a systems perspective, uncertainty should be treated as an inherent property of the data pipeline and communicated in ways that support informed decision making [15].

Interoperability between exposure models and health data systems is another important consideration. Personalized exposure metrics are most useful when they can be linked to health outcomes in epidemiological studies or clinical care. This linkage requires standardized exposure data formats, temporal aggregation, and privacy preserving record matching. Without such infrastructure, wearable and IoT based exposure data may remain isolated from the very health decisions they are intended to inform. Cross disciplinary collaboration among exposure scientists, computer scientists, and health informatics specialists is therefore critical to the design of integrated exposure assessment platforms [16].

5. Deployment, Infrastructure and Sustainability

Deployment of wearable and IoT based indoor air pollutant monitoring systems involves more than installing sensors. Building characteristics, occupant behavior, and local infrastructure shape the feasibility and representativeness of monitoring campaigns. Residential buildings constructed with different materials may emit different profiles of volatile organic compounds, including formaldehyde and other compounds associated with adverse health outcomes [18]. Older buildings may have lower air exchange rates but also lower emissions from some modern materials, while newer energy efficient buildings may reduce ventilation and contribute to pollutant accumulation. Building age, renovation history, and heating and cooking systems all influence indoor concentrations and must be documented as part of any deployment design [17].

Community based deployments often rely on participatory sensing in which residents or workers operate and maintain the devices. This approach can increase spatial coverage and foster environmental awareness, but it also raises questions about data quality and participant burden. Devices that require frequent charging, recalibration, or firmware updates may be abandoned or misused, leading to biased data. Sustainable deployment strategies must account for maintenance logistics, technical support, and the social context of participation. In low resource settings, unreliable electricity and internet access can further constrain deployment, requiring offline data storage and opportunistic synchronization. The success of a monitoring program depends as much on these sociotechnical factors as on the sensor hardware itself [19].

Infrastructure choices also affect energy use and environmental sustainability. Large networks of battery powered devices create electronic waste and require periodic battery replacement. Solar powered or mains powered stationary nodes reduce battery waste but may not be feasible in all indoor environments. Edge computing can reduce cloud energy consumption by

processing data locally, but it increases the energy demand of gateway devices. Life cycle assessment of monitoring infrastructure is rarely performed, yet it is relevant to the environmental footprint of exposure assessment itself. Designers should consider modular hardware, repairability, and end of life recycling as integral components of sustainable monitoring systems [20].

Scalability is another deployment concern. A pilot study in a few homes may demonstrate technical feasibility, but scaling to hundreds or thousands of households requires interoperable data management, automated quality control, and robust communication protocols. Cloud based platforms can support large scale data collection, but they may introduce latency, privacy risks, and recurring costs. Edge and fog computing architectures can distribute data processing and reduce dependence on central infrastructure, but they require more sophisticated software and configuration management. The optimal balance between centralized and distributed processing depends on the specific use case, available resources, and long term institutional support [21].

6. Robustness and Data Quality Assurance

Robustness in wearable and IoT based indoor monitoring systems refers to the ability to maintain acceptable performance under varying environmental conditions, user behaviors, and network disruptions. Robustness is related to but distinct from accuracy. A system may produce accurate readings under ideal laboratory conditions yet fail in real indoor environments due to power interruptions, sensor drift, or communication outages. Achieving robustness requires redundancy, adaptive calibration, and graceful degradation. For example, if a stationary node loses connectivity, nearby wearable sensors can continue to provide partial coverage, and data recovery procedures can reconstruct missing periods when connectivity resumes. Such resilience is especially important for long term exposure studies in which gaps in data can bias estimates of cumulative exposure [22].

Data quality assurance should be framed as a continuous process rather than a one-time validation step. At ingestion, automated checks can flag implausible values, sensor saturation, and sudden jumps that may indicate malfunction. During processing, statistical models can compare sensor signals across colocated devices and detect systematic offsets. Periodic recalibration can correct drift using reference measurements or known environmental conditions. At the analysis stage, sensitivity analyses can assess how data quality issues affect exposure estimates and downstream health models. This layered approach to quality assurance is analogous to practices in environmental regulatory monitoring, but it must be adapted to the lower precision and higher variability of low cost sensors [23].

The human dimensions of data quality are also important. Users may move sensors, block air intakes, or place devices near strong sources such as toasters or cleaning products, producing measurements that are not representative of breathing zone concentrations. Participant training, clear placement instructions, and remote monitoring of sensor status can mitigate these problems. In community deployments, building trust and providing feedback can improve compliance and data completeness. However, excessive user responsibility can reduce accessibility for elderly persons, people with disabilities, or those with limited technical literacy. Designing systems that minimize required user intervention while maintaining contextual awareness is a key challenge for equitable monitoring [11].

7. Privacy, Fairness and Governance

Wearable and IoT based indoor air pollutant monitoring generates sensitive personal data. Location traces, time activity patterns, and even pollutant concentrations can reveal information about daily routines, household composition, and health related behaviors. For example, carbon monoxide peaks may indicate cooking practices, while particulate matter increases could be associated with smoking or candle use. If these data are linked to health records or shared with insurers, employers, or landlords, they could be used to discriminate against individuals or households. Privacy frameworks such as contextual integrity emphasize that data flows should respect the norms of the context in which they are produced [21]. Applying this principle to environmental monitoring means that users should have meaningful control over who accesses their exposure data and for what purposes.

The European Union General Data Protection Regulation and similar laws impose requirements for data minimization, purpose limitation, and informed consent in many jurisdictions [22]. However, environmental sensor data may not always be treated as personal data under existing legal frameworks, particularly when aggregated or anonymized. Yet anonymization of location rich exposure data is notoriously difficult, and re-identification risks are significant. Governance mechanisms must therefore go beyond formal compliance to include ethical review, community participation, and transparent data stewardship. Data sharing agreements should specify whether data will be used for research, public health surveillance, or commercial purposes, and they should provide mechanisms for withdrawal and deletion [23].

Fairness is a central concern in personalized exposure assessment. The benefits of wearable and IoT based monitoring are not evenly distributed. High income households may be more likely to purchase commercial air quality monitors and receive personalized feedback, while low income households may experience higher indoor pollutant burdens due to older housing, denser occupancy, and proximity to outdoor pollution sources [24]. If monitoring systems are designed without attention to these disparities, they may reinforce existing environmental health inequities by generating data that primarily represents more advantaged populations. Community based monitoring initiatives can counter this trend by prioritizing recruitment in underserved areas and returning results in culturally appropriate formats. Fairness also requires that algorithms used for exposure classification and source attribution do not systematically misclassify pollutants in certain housing types or demographic groups due to unrepresentative training data [25].

Governance of IoT based environmental monitoring extends beyond data protection to include device certification, sensor performance standards, and liability for inaccurate measurements. Consumer devices often lack clear performance specifications, making it difficult for users to know whether a reading is reliable enough to guide health decisions. Regulatory agencies in some regions have begun developing nonregulatory performance targets for low cost sensors, but these frameworks are still evolving. Liability for harms caused by inaccurate exposure information is unclear, particularly when data are processed by third party platforms. Clear governance frameworks can help build public trust and encourage the adoption of monitoring systems in settings such as schools, hospitals, and public housing [13].

8. Policy Implications and Research Directions

The emergence of wearable and IoT based indoor air pollution monitoring has significant policy implications. Public health agencies could use these systems to identify hot spots of indoor exposure, evaluate the effectiveness of ventilation interventions, and target resources

to vulnerable communities. However, such applications require standardized data quality protocols and interoperability with existing regulatory monitoring networks. Policy makers should consider investing in reference grade indoor monitoring in selected buildings to anchor the calibration of low cost sensor networks. This hybrid approach would combine the spatial richness of low cost devices with the accuracy of reference instruments, providing a stronger evidence base for indoor air quality standards and guidelines [4].

Indoor air quality is rarely regulated at the same level as outdoor air quality in most countries. Wearable and IoT based monitoring could generate the exposure data needed to support the development of indoor air quality guidelines for homes, schools, and workplaces. Such data could also inform building codes and ventilation standards. For example, if large scale monitoring demonstrates that certain building materials consistently produce elevated volatile organic compound concentrations under typical ventilation rates, policy makers could strengthen material emission standards or require mechanical ventilation in new construction. The required reference to residential volatile organic compound emissions from building materials illustrates the type of evidence that monitoring and exposure assessment can provide for regulatory action [18].

Research directions should address several persistent gaps. First, long term field studies are needed to characterize sensor performance over months and years, not just days or weeks. Second, methods for calibrating sensors across diverse indoor environments must be improved, perhaps through transfer learning and domain adaptation. Third, exposure models should be developed that explicitly incorporate uncertainty and allow for individual level validation against reference instruments. Fourth, privacy preserving data architectures, such as federated learning and differential privacy, should be evaluated for their impact on data utility and fairness. Fifth, interdisciplinary research should examine how personalized exposure feedback influences behavior, health literacy, and environmental justice. These directions require collaboration among environmental engineers, computer scientists, epidemiologists, and social scientists [20].

The integration of wearable and IoT based monitoring into clinical and public health practice will also require new forms of evidence. Randomized controlled trials comparing personalized exposure feedback with standard care could clarify whether such systems improve health outcomes or reduce pollutant exposures. Observational studies linking continuous personal exposure data to biomarkers of effect can strengthen causal inference in environmental epidemiology. At the same time, researchers should remain attentive to the risk that continuous monitoring creates anxiety or stigmatization, particularly for households with elevated pollutant levels. Ethical oversight and user centered design should be integral to these investigations [24].

From an infrastructure perspective, future systems should be designed for interoperability and longevity. Open hardware platforms, standard data formats, and modular sensor replaceability can reduce vendor lock in and extend the useful life of devices. Cloud services should support data portability and user deletion rights. Edge computing capabilities should be sufficient to support local calibration and anomaly detection without depending on continuous internet connectivity. These technical requirements are not merely engineering details; they shape the governance and equity of personalized exposure assessment. A well designed monitoring system can empower individuals and communities with knowledge about their environmental conditions, whereas a poorly designed system may generate noise, erode trust, and widen health disparities [15].

9. Conclusion

Wearable and IoT based monitoring of indoor air pollutants represents a major shift in environmental exposure assessment. By moving measurement from sparse stationary sites to the microenvironments where people spend most of their time, these technologies can improve the spatial and temporal resolution of exposure data and support more precise health research and risk communication. However, the benefits of these systems depend on more than the availability of low-cost sensors. They require careful attention to system architecture, calibration, contextual data fusion, deployment logistics, robustness, privacy, fairness, and governance. Sensor drift, cross sensitivity, and placement effects introduce uncertainty that must be quantified and communicated. Data generated by wearable devices are both valuable and sensitive, and their use must be governed by ethical and legal frameworks that protect individual and community interests.

The path forward involves building integrated infrastructures that combine wearable devices, stationary indoor nodes, edge computing, and cloud based services within interoperable and privacy preserving architectures. Such infrastructures should support continuous data quality assurance and allow for the inclusion of reference measurements to anchor low-cost sensor networks. They should also be designed with equity in mind, ensuring that underserved communities can participate in and benefit from environmental monitoring. Policy makers, researchers, and technology developers must work together to establish performance standards, data governance frameworks, and sustainable deployment models. Only through such coordinated efforts can wearable and IoT based systems fulfill their promise as tools for personalized environmental exposure assessment and environmental health equity.

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