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¹ Department of Civil Engineering, Ballari Institute of Technology & Management, Ballari.

² Department of Civil Engineering, AMC Engineering College, Bangalore

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INDOOR AIR QUALITY IN CLASSROOM ENVIRONMENTS: A SCOPING REVIEW

*Ashwini R¹, Surya Chitthara K.C¹, Abhishek M¹, Sneha¹, Vinod N², Prema T²

ABSTRACT

This scoping review synthesises 33 peer-reviewed studies (2012–2026) on classroom indoor air quality (IAQ), identified through OpenAlex and screened using PRISMA-ScR. The review addresses IAQ parameters, occupancy effects, monitoring technologies, and research gaps. CO₂ was the most consistently monitored parameter; exceedances above 1000 ppm were documented in 19 of 28 empirical studies, with peaks reaching 2200 ppm in naturally ventilated classrooms. PM_{2.5} and PM₁₀ concentrations increased 2.3–3.4-fold during occupied periods. IoT-based monitoring has improved temporal resolution substantially, and machine learning now predicts threshold exceedances with >85% accuracy. Six research gaps were identified: single-parameter monitoring dominance, absence of controlled dual-room comparative studies, underreporting of exposure duration, lack of simultaneous occupancy–ventilation experimental arms, absence of real-time alerts, and underrepresentation of South Asian environments. These gaps inform the design of a dual-node IoT system deployed in academic staff rooms in Bellary, Karnataka, India.

KEYWORDS: Indoor Air Quality, Classroom Environment, Occupancy Effects, CO₂ Monitoring, Particulate Matter, IoT-Based Monitoring

1. INTRODUCTION

Classroom IAQ is a substantive public health challenge. Occupant densities in educational spaces routinely exceed those of comparable non-residential environments, generating metabolic CO₂ loads and particle resuspension rates that ventilation systems frequently fail to compensate. Satish et al. (2012) demonstrated that CO₂ above 1000 ppm impairs decision-making; Deng et al. (2023) quantified a 3% rise in illness-related absenteeism per 100 ppm CO₂ increase; and Wargocki and Wyon (2012) showed ventilation improvements alone produced up to 15% gains in student task performance.

CO₂ and particulate matter (PM_{2.5}, PM₁₀) are the parameters most consistently implicated in IAQ deterioration. Chatzidiakou et al. (2015) validated CO₂ as a ventilation proxy across 14 UK classrooms. Field studies across Europe

document 1000 ppm exceedances as routine during occupied periods. Rosbach et al. (2015) reported PM₁₀ levels 3.4× higher during occupied periods; Zee et al. (2016) documented PM_{2.5} rising from ~8 µg/m³ pre-class to 22–35 µg/m³ during active teaching. The shift to low-cost IoT monitoring has substantially advanced the field's capacity, yet a critical gap persists: teacher perception consistently fails to track measured pollutant levels (Canha et al., 2024), undermining reliance on behavioural ventilation management without automated alerts.

Four structural gaps motivate this study: no controlled dual-room comparative study exists isolating occupancy as the sole variable; occupancy and ventilation effects have been investigated as separate streams; real-time alert systems remain absent from IAQ deployments; and South Asian academic environments are significantly underrepresented. This paper

reports a PRISMA-ScR scoping review of 33 studies, providing the empirical foundation for a dual-node IoT system deployed in Bellary, Karnataka.

2. METHODOLOGY

2.1 Review Framework

This study employs a scoping review methodology following Arksey and O'Malley (2005), refined by Levac et al. (2010), and conducted per PRISMA-ScR guidelines (Tricco et al., 2018). The scoping design was selected to map the range of monitoring practices, parameters, and conditions across classroom IAQ research rather than appraise a specific intervention. The multidisciplinary character of the field—spanning environmental engineering, building science, sensor technology, and public health—further supports this approach, which accommodates heterogeneous study designs within a unified analytical framework.

2.2 Research Questions

RQ1: What IAQ parameters are most consistently monitored, and what are their typical levels and exceedance patterns?

RQ2: How does occupancy influence IAQ, and what is the evidence on exposure duration above recommended thresholds?

RQ3: What monitoring technologies and IoT platforms have been deployed, and how have low-cost sensors been validated?

RQ4: What methodological and contextual gaps remain, and how does the present experimental study respond to them?

2.3 Search Strategy and Selection

A structured OpenAlex search was conducted in April 2026 using: ("indoor air quality" OR "IAQ" OR "CO₂" OR "PM_{2.5}") AND ("classroom" OR "school" OR "university") AND ("monitoring" OR "IoT" OR "sensors" OR "occupancy"). This yielded 1,150 records; after filtering, 496 underwent title screening, 48 abstract screening, and 28 met full eligibility. Six additional foundational studies were incorporated as supplementary references, giving a total analytical dataset of 33 studies. Inclusion required peer-reviewed studies (2014–2026) reporting quantitative IAQ measurements in classroom settings. Studies relying solely on surveys, purely theoretical work, and non-English publications were excluded.

2.4 Data Extraction and Synthesis

Data were extracted into a structured framework capturing: study type, setting, monitoring technology, IAQ parameters, occupancy consideration, IoT

integration, key findings, and thematic classification. Five major themes were identified: IAQ parameters (T1), occupancy impact (T2), monitoring technologies (T3), health and performance implications (T4), and research gaps (T5). Gap identification was derived quantitatively from the distribution of studies across T1–T4, producing six formally characterised gaps (Table 1).

[Insert Table 1: Research Gaps and Experimental Design Responses]

3. LITERATURE REVIEW

3.1 IAQ Parameters in Classroom Environments (RQ1)

Classroom IAQ cannot be adequately characterised by any single parameter; CO₂, PM_{2.5}, PM₁₀, temperature, and relative humidity each capture distinct dimensions, and their simultaneous exceedance has been documented across multiple studies.

CO₂ is the most widely monitored parameter. Studies report exceedances above 1000 ppm as routine: Pereira et al. (2014) documented frequent exceedances in Portuguese classrooms despite acceptable thermal comfort; Stazi et al. (2017) recorded CO₂ rising from ~400 ppm to >1800 ppm within a single 50-minute lesson under natural ventilation; Fuoco et al. (2015) reported peaks approaching 2200 ppm in Italian winter classrooms; and Fedele et al. (2025) confirmed these exceedances persist a decade later. Johnson et al. (2018) demonstrated exceedances even in mechanically ventilated UK classrooms when occupancy exceeded design capacity. Rajagopalan et al. (2021) found Australian students were exposed above 1000 ppm for a mean of 3.2 hours per school day.

Particulate matter monitoring reveals exposure partially independent of CO₂ dynamics. Rosbach et al. (2015) found PM₁₀ 3.4× higher during occupied periods, driven by resuspension. Zee et al. (2016) documented PM_{2.5} peaks of 22–35 µg/m³ from baselines of ~8 µg/m³, with a 38% reduction following filter installation. UNESP et al. (2026) reported PM_{2.5} reaching 43.75 µg/m³ in Brazilian classrooms—~9× the WHO 24-hour guideline. Jovanovic et al. (2014) confirmed indoor PM exceeded outdoor levels in Serbian classrooms.

Thermal parameters modulate IAQ in ways single-parameter monitoring cannot capture. Caciara et al. (2024) demonstrated that CO₂, PM, and

VOCs simultaneously exceeded guideline limits in Romanian classrooms during periods when thermal comfort was within acceptable ranges. Critically, Canha et al. (2024) showed that across 171 monitored sessions, teacher IAQ perception correlated only with temperature, while CO₂ exceedances in 27% of sessions and PM₁₀ exceedances in 32% went entirely undetected—confirming that behavioural ventilation management without real-time feedback is structurally inadequate.

3.2 Occupancy Impact on IAQ (RQ2)

Occupancy drives IAQ deterioration through two pathways: a metabolic pathway generating CO₂ proportional to occupant count, and an activity-driven pathway causing PM resuspension. Wang et al. (2017) reported $r = 0.87$ ($p < 0.001$) between occupant count and CO₂ across a university building. Ramos et al. (2023) operationalised this as a rise-rate threshold—~15 ppm/min reliably indicating occupancy above 60% of capacity. Hama et al. (2023) quantified occupancy-driven increases of ~150% for CO₂ and ~230% for PM₁₀, indicating PM is more occupancy-sensitive. Kasapoglu et al. (2023) documented progressive accumulation from morning to evening, confirming occupancy effects do not reset between class periods. Rajagopalan et al. (2021) established that exposure duration above threshold is a more sensitive health indicator than peak concentration—a finding that directly informs the present study's analysis protocol.

No prior study has isolated occupancy through controlled simultaneous dual-room comparison under matched environmental conditions. Every occupancy study in the dataset monitors a single room or compares rooms at different times, making clean attribution of IAQ differences to occupancy alone impossible. The present study's Batch B8 design addresses this directly.

3.3 Monitoring Technologies and IoT-Based IAQ Systems (RQ3)

Conventional spot-measurement approaches fail to characterise occupancy-driven IAQ dynamics. Dorizas et al. (2014) demonstrated that periodic measurements significantly underestimated peak CO₂ relative to continuous logging. Concilio et al. (2024) identified vertical CO₂ stratification introducing systematic bias when sensors are placed at non-breathing height. The shift to low-cost continuous IoT monitoring has addressed temporal resolution. Weyers et al. (2017) validated low-cost

sensors as adequate for classroom IAQ applications; Wang et al. (2017) demonstrated $r = 0.87$ correlation and established the WiFi-to-cloud architecture; Ge et al. (2025) extracted 245 million measurements across 3,600 school sensors, revealing CO₂ peaks exceeding 5,080 ppm invisible to spot sampling; and Apostolopoulos et al. (2025) achieved >85% accuracy in predicting exceedances 15–20 minutes in advance using LSTM models.

A persistent gap across all reviewed IoT deployments is the absence of embedded real-time alert mechanisms. All six IoT studies in the dataset operated in passive data-collection mode. Apostolopoulos et al. (2025) identified this as the primary translational barrier between monitoring and management. The present study addresses this through a CO₂-triggered LED and LCD alert system embedded within each node, activating at 1000 ppm and converting each logger from passive to active management instrument.

3.4 Research Gaps (RQ4)

G1 – Single-parameter monitoring dominance: 10 of 33 studies monitored CO₂ exclusively or with temperature only; only 8 achieved five-parameter monitoring. Compound exceedances during CO₂-acceptable periods (Caciara et al., 2024) demonstrate the consequence.

G2 – Absence of controlled dual-room simultaneous comparative studies: every occupancy study in the dataset monitors a single room or rooms at different times. Attribution of IAQ differences to occupancy without matched controls is confounded by building and environmental variables.

G3 – Exposure duration underreported: only Rajagopalan et al. (2021) reported cumulative threshold exceedance duration as a primary metric. All other studies reported peak or mean concentrations, systematically understating health significance.

G4 – Occupancy and ventilation as separate streams: no study implements both as controlled parallel experimental arms. Their interaction on IAQ outcomes remains uncharacterised.

G5 – Real-time alerts absent: none of the six IoT-enabled studies embedded threshold-triggered physical alerts at room level, identified by Apostolopoulos et al. (2025) as the key translational gap.

G6 – South Asian environments absent: 19 of 33 studies are from European contexts; none are from South Asia. Building typologies, occupancy densities, and ventilation practices in Indian academic buildings differ substantially from European study contexts.

4. RESULTS

CO₂ exceedances above 1000 ppm were documented in 19 of 28 empirical studies during occupied periods, with peaks from 1500 to >5000 ppm depending on ventilation type and occupant density. Parameter coverage was uneven: CO₂ monitored in 28 studies; PM in 18; temperature in 16; relative humidity in 12; full five-parameter monitoring in fewer than 8. IoT-based monitoring was fully implemented in 6 studies, partially in 4, and absent in 23. Geographically, 19 studies were European, 5 East Asian or Australian, 3 South American or African, and none South Asian.

PM_{2.5} exceedances above WHO guidelines were reported in multiple studies (Zee et al., 2016: 22–35 µg/m³; UNESP et al., 2026: 43.75 µg/m³). Multi-parameter studies demonstrated frequent co-occurrence of CO₂ and PM exceedances during periods that single-parameter monitoring would classify as acceptable (Dorizas et al., 2014; Caciara et al., 2024). Health evidence consistently linked CO₂ and PM exposure to cognitive impairment (Satish et al., 2012), increased absenteeism (Deng et al., 2023), and reduced performance (Wargocki and Wyon, 2012). A clear chronological transition from spot measurements (pre-2017) to continuous IoT monitoring (post-2017) was evident across the dataset, with no reviewed IoT study incorporating embedded real-time alert systems.

5. DISCUSSION

The strength and consistency of the occupancy–IAQ relationship across 33 studies establishes occupant metabolic load as the dominant driver of IAQ deterioration, overriding building-specific ventilation design differences. The $r = 0.87$ correlation (Wang et al., 2017) is matched in magnitude by PM increases in naturally ventilated European schools (Rosbach et al., 2015; Zee et al., 2016), confirming the occupancy effect is neither technology-specific nor climate-specific. Any ventilation strategy that does not dynamically respond to actual occupancy will produce predictable, systematic IAQ failures. The temporal dimension—pollutant accumulation reflecting integrated occupancy history across the school day—means static design specifications

cannot guarantee adequate IAQ, and any monitoring protocol not capturing the full diurnal profile will systematically underestimate cumulative exposure.

The most consistent methodological limitation is treating CO₂ as a sufficient IAQ characterisation parameter. Dorizas et al. (2014) and Caciara et al. (2024) demonstrated compound exceedances during CO₂-acceptable periods; Canha et al. (2024) showed PM₁₀ exceeded limits in 32% of sessions while teacher perception remained unresponsive. A monitoring system reporting only CO₂ simultaneously fails to detect co-occurring PM exceedances, understating health risk in proportion to independent PM exceedance frequency. The present study's five-parameter node specification responds directly to this gap.

The most consequential gap is translational: six IoT studies collectively deployed hundreds of sensors without providing a single room-level alert enabling immediate ventilation response. In naturally ventilated classrooms, the lowest-cost intervention—opening a window—requires only that the teacher know when to act. The LED and LCD alert system embedded in each monitoring node closes this gap, transforming passive loggers into actionable management instruments at negligible additional hardware cost. Combined with exposure duration analysis as a primary metric (directly addressing G3), five-parameter simultaneous sensing (G1), matched dual-room deployment (G2), parallel occupancy–ventilation experimental arms (G4), and empirical data from Bellary, Karnataka (G6), the present study addresses all six identified gaps within a single experimental framework—the first study in the reviewed literature to do so.

Limitations include reliance on a single database (OpenAlex), single-reviewer screening, and the supplementary inclusion of five studies outside the formal PRISMA process. The geographical concentration of the dataset in European settings limits generalisability to non-European contexts.

6. CONCLUSION

Classroom IAQ is governed by quantitatively consistent relationships: occupancy drives CO₂ accumulation that ventilation systems frequently cannot compensate; PM concentrations respond through resuspension and activity-driven mechanisms partially independent of CO₂; and health and cognitive consequences are measurable

and educationally significant. CO₂ exceedances above 1000 ppm were documented in 19 of 28 empirical studies, with peaks reaching 2200 ppm in naturally ventilated classrooms and exceeding 5000 ppm in large-scale IoT datasets. The monitoring technology base has matured—low-cost sensors validated against reference instruments, WiFi-to-cloud architectures enabling real-time data access, and machine learning predicting exceedances with >85% accuracy. What has not matured is the translational step from data collection to occupant management: no reviewed IoT deployment embedded room-level alerts despite clear evidence that teacher perception cannot substitute for measurement.

Six research gaps were identified through quantitative analysis of the 33-study dataset, none previously addressed simultaneously. The dual-node IoT monitoring system deployed in Bellary, Karnataka responds to all six within a single framework. Future studies should extend this framework to multi-building and multi-city deployments across South Asian, African, and South American educational contexts to establish whether European occupancy–IAQ relationships are transferable across climatic and construction typologies.

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