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Evaluation of Natural Ventilation Influence on Indoor Air Quality in Small Academic Rooms using an IOT-Based Monitoring System

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ABSTRACT

Indoor air quality (IAQ) in academic environments has gained critical importance due to its direct implications on student cognitive performance, health, and well-being. Small academic rooms, characterized by limited floor area, high occupant density, and constrained architectural configurations, present unique challenges for maintaining adequate air quality through natural ventilation alone. This study presents a comprehensive evaluation of natural ventilation influence on indoor air quality parameters within small academic rooms at an Indian university campus, employing a custom-designed Internet of Things (IoT)-based real-time monitoring system.

A network of low-cost, calibrated multi-parameter sensor nodes was deployed across twelve classrooms of varying orientations, window-to-floor-area ratios (WFR: 0.08 to 0.22), and occupancy levels (15 to 45 students). Each node continuously measured carbon dioxide (CO2, ppm), particulate matter (PM2.5 and PM10, ug/m3), temperature (degC), relative humidity (%), volatile organic compounds (VOC, ppb), and formaldehyde (HCHO, ug/m3) at one-minute intervals over a monitoring period of nine months spanning all three climatic seasons (winter, summer, and monsoon).

Results indicate that CO2 concentrations exceeded the ASHRAE 62.1 threshold of 1000 ppm during 68.4% of occupied hours in rooms with WFR below 0.12 and adverse wind conditions. PM2.5 levels surpassed the WHO 24-hour guideline of 15 ug/m3 in 54.2% of monitored sessions during the pre-monsoon season, attributable to outdoor particulate infiltration through open windows. Rooms with cross-ventilation configurations demonstrated 34.7% lower mean CO2 concentrations compared to single-sided ventilation arrangements. Occupancy density emerged as the strongest predictor of CO2 accumulation (R2 = 0.87), followed by wind speed (R2 = 0.73) and window opening area (R2 = 0.68). Regression models and machine learning classifiers (Random Forest, AUC = 0.94) were developed to predict IAQ category (Good/Moderate/Poor) using environmental and architectural input parameters.

The IoT system demonstrated a mean absolute error (MAE) of 28.4 ppm for CO2 prediction and 1.8 ug/m3 for PM2.5 estimation after field calibration against reference instruments. Findings highlight critical deficiencies in current natural ventilation practices and provide evidence-based recommendations for window design, occupancy scheduling, and supplementary mechanical ventilation strategies. This research contributes directly to sustainable building design and healthy learning environment policy in tropical climate zones.

1. INTRODUCTION

Indoor air quality (IAQ) is recognized as a critical determinant of occupant health, productivity, and cognitive function, particularly within educational settings where students spend six to eight hours per day in enclosed spaces [1, 2]. The World Health Organization (WHO) reports that poor indoor air quality contributes to approximately 3.8 million premature deaths annually, with low- and middle-income countries disproportionately affected due to inadequate ventilation infrastructure [3]. In academic institutions across tropical developing nations, natural ventilation remains the predominant and often sole mechanism for maintaining air quality owing to economic constraints, architectural heritage, and climate-suitability considerations [4].

Small academic rooms, typically defined as spaces with floor areas between 30 and 80 square meters accommodating 20 to 50 students, are particularly susceptible to IAQ degradation [5]. The confluence of high metabolic CO2 generation, limited volumetric air exchange, and seasonal outdoor air pollution creates cyclical patterns of poor air quality that are poorly documented in the existing literature for South Asian climatic contexts [6]. While extensive research has been conducted in temperate European and North American classrooms [7, 8, 9], studies addressing tropical and subtropical classroom environments — where stack effect ventilation is minimal and wind-driven ventilation is intermittent — remain comparatively scarce [10].

The emergence of Internet of Things (IoT) technology has democratized environmental monitoring by enabling deployment of dense sensor networks at substantially lower cost than traditional reference monitoring stations [11, 12]. Low-cost electrochemical and optical sensors for CO2, particulate matter, VOCs, and microclimatic parameters can be integrated into compact, Wi-Fi-enabled devices capable of continuous data streaming to cloud platforms [13]. However, the accuracy, drift characteristics, and field calibration requirements of such sensors in high-humidity, high-particulate tropical environments require systematic validation [14, 15].

Several studies have investigated the relationship between window opening behavior and IAQ in classrooms [16, 17]. Stabile et al. [18] demonstrated that intermittent window opening in Italian primary schools reduced CO2 concentrations by 40% during break periods. Mumovic et al. [19] established correlations between ventilation rates and student performance on standardized cognitive tests. Dorizas et al. [20] developed ventilation efficiency metrics specific to Mediterranean classroom geometries.However, none of these investigations have employed real-time IoT infrastructure to capture minute-by-minute IAQ dynamics under natural ventilation in South Asian academic environments.

This study addresses the identified knowledge gap by deploying a custom IoT monitoring network across twelve representative classrooms at a South Indian university campus. The primary objectives are:
(i) to characterize IAQ parameter distributions under natural ventilation across three climatic seasons; (ii) to quantify the influence of architectural variables (window-to-floor ratio, orientation, room geometry) and occupancy patterns on IAQ; (iii) to validate low-cost sensor performance against reference instruments under tropical field conditions; and (iv) to develop predictive models for IAQ classification applicable to real-time ventilation management systems.

The remainder of this paper is organized as follows: Section 2 reviews relevant literature; Section 3 describes the experimental methodology and IoT system architecture; Section 4 presents monitoring results and statistical analyses; Section 5 discusses findings in the context of existing standards and prior research; and Section 6 summarizes conclusions and practical recommendations.

2. LITERATURE REVIEW

2.1 Indoor Air Quality in Educational Buildings

The relationship between classroom IAQ and learning outcomes has been studied for over three decades. Wargocki and Wyon [21] conducted controlled chamber studies demonstrating that doubling outdoor air supply rates improved school children's performance on tasks related to reading, arithmetic, and concentration by 8-14%. Satish et al. [22] reported cognitive function impairment at CO2 concentrations above 1000 ppm, with statistically significant declines in decision-making scores at 2500 ppm compared to 550 ppm reference conditions. These findings fundamentally challenge the traditional view that CO2 serves merely as an indicator of ventilation adequacy rather than as an independent cognitive stressor.

Systematic reviews by Mendell and Heath [23] and Kim and Lemasters [24] identified associations between poor classroom IAQ and increased absenteeism, respiratory symptoms, and doctor visits among elementary and secondary school students. Particulate matter exposure in classrooms has been linked to exacerbation of asthma and allergic rhinitis [25]. VOC concentrations, originating from building materials, cleaning products, and human activities, exhibit complex seasonal patterns in naturally ventilated environments [26].

2.2 Natural Ventilation in Tropical Climates

Natural ventilation in tropical buildings relies primarily on wind-driven cross-ventilation and, to a lesser extent, thermal buoyancy (stack effect) [27]. In equatorial and tropical climates, the weak stack effect due to small indoor-outdoor temperature differentials necessitates wind-driven ventilation as the dominant mechanism [28]. Givoni [29] established foundational relationships between wind speed, window configuration, and indoor air change rates in tropical buildings, demonstrating that cross-ventilation could achieve 10-30 air changes per hour (ACH) under favorable wind conditions, far exceeding the ASHRAE minimum of 0.35 ACH for occupied spaces.

Singh et al. [30] evaluated natural ventilation effectiveness in Indian educational buildings using tracer gas techniques, reporting mean ACH values of 1.2 to 4.8 in classrooms with WFR between 0.10 and 0.18. Thermal comfort surveys conducted simultaneously revealed occupant dissatisfaction with both air movement and thermal conditions during summer months when outdoor temperatures exceeded 38ºC. Kubota et al. [31] investigated wind-driven ventilation in Malaysian single-story school buildings using computational fluid dynamics (CFD) simulations, validating their models against measured pressure coefficients and identifying optimal window placement configurations for cross-ventilation enhancement.

2.3 IoT-Based Environmental Monitoring Systems

The application of IoT technology to indoor environmental monitoring has expanded significantly following advances in MEMS-based gas sensors, microcontrollers, and low-power wireless communication protocols [32]. Platforms such as Arduino, Raspberry Pi, and ESP32 have enabled researchers to develop custom monitoring nodes at costs of USD 50-150 per unit, compared to USD 5,000-50,000 for reference-grade instruments [33]. Studies by Bhattacharya et al. [34] and Marques et al. [35] demonstrated successful deployment of ESP32-based IAQ monitors in occupied buildings, achieving measurement uncertainties within 10% of reference values after temperature and humidity compensation.

NDIR (Non-Dispersive Infrared) sensors such as the SenseAir S8 and Sensirion SCD40 have emerged as reliable low-cost CO2 measurement devices, with reported accuracies of +/- 50 ppm over their operational range of 400-5000 ppm [36]. Optical particle counters for PM2.5 and PM10, including the Plantower PMS5003 and Honeywell HPM series, have been extensively characterized against gravimetric reference methods, showing mass concentration correction factors ranging from 0.6 to 2.1 depending on aerosol composition and relative humidity [37]. Electrochemical sensors for NO2, O3, and VOCs exhibit significant cross-sensitivity and temperature-dependence requiring careful field calibration protocols [38].Research Gaps

Despite substantial progress in both IAQ characterization and IoT monitoring technologies, several critical gaps remain. First, comprehensive seasonal IAQ datasets from naturally ventilated tropical academic buildings monitored with validated IoT systems are absent from the peer-reviewed literature. Second, the interaction effects between monsoon-season outdoor air quality, high relative humidity, and natural ventilation infiltration on classroom IAQ have not been systematically quantified. Third, machine learning approaches for real-time IAQ prediction in academic buildings have been demonstrated only in mechanically ventilated settings with reference-grade sensor data. This study addresses all three gaps through a nine-month field investigation.

3. METHODOLOGY

3.1 Study Site Description

The study was conducted at a technical university campus located in Anekal, Karnataka, India (12.71 deg N, 77.69 deg E, elevation 890 m above sea level). The campus experiences a tropical savanna climate (Koppen classification: Aw) characterized by a dry summer season (March-May, mean maximum temperature 34.2 degC), a northeast monsoon period (June-September, mean relative humidity 82%), and a comparatively mild winter (November-

February, mean minimum temperature 14.6 degC). Prevailing winds during the monitoring period were predominantly from the southwest at 2.8 m/s mean speed (ASOS station data, KIA Bengaluru).

Twelve classrooms were selected from four academic buildings constructed between 1998 and 2018, spanning different architectural generations and ventilation philosophies. Room floor areas ranged from 42 to 78 m2, with ceiling heights of 3.2 to 4.0 m. Window-to-floor-area ratios varied from 0.082 to 0.218. Six rooms featured single-sided ventilation (windows on one wall only) and six had cross-ventilation potential (windows on opposing or perpendicular walls). Classroom orientations covered all four cardinal directions. Occupancy schedules comprised regular 50-minute lecture periods with 10-minute intermissions, typically generating two to four occupied periods per day per room.

3.2 IoT Monitoring System Architecture

Each monitoring node consisted of a custom-designed printed circuit board (PCB) integrating the following sensors: (i) Sensirion SCD41 NDIR CO2 sensor (measurement range 400-5000 ppm, accuracy +/- 40 ppm); (ii) Plantower PMS5003 laser particle counter for PM1.0, PM2.5, and PM10 (range 0-1000ug/m3); (iii) Sensirion SHT31-D for temperature and relative humidity (accuracy +/- 0.3 degC, +/- 2% RH); (iv) SGP30 MOX sensor for total VOCs and estimated CO2-equivalent; and (v) MEMS formaldehyde sensor (AMS AS4521, range 0-1 ppm). An ESP32-WROOM-32 microcontroller managed sensor acquisition, local data logging to a 16 GB microSD card, and Wi-Fi transmission to the cloud server via MQTT protocol.

Data was acquired at one-minute intervals during scheduled monitoring hours (08:00-18:00 IST) and at five-minute intervals during unoccupied periods. Nodes were powered via standard 5V USB wall adapters with lithium polymer battery backup (2600 mAh) providing 8 hours of autonomous operation during power outages. The cloud infrastructure comprised a Raspberry Pi 4 Model B server running Mosquitto MQTT broker, InfluxDB time-series database, and Grafana dashboard for real-time visualization accessible to building managers via a web interface.

3.3 Sensor Calibration and Validation

Prior to field deployment, all sensor nodes underwent a three-stage calibration protocol in a temperature-controlled environmental chamber. Stage 1 involved fresh-air baseline calibration for CO2 sensors at 415 ppm reference gas. Stage 2 comprised multi-point calibration for PM sensors against a TSI DustTrak II reference photometer using locally generated aerosol (ammonium sulfate and Arizona road dust). Stage 3 involved temperature and humidity characterization across the range 18-40 degC and 40-95% RH to derive correction coefficients.

Field validation was performed by co-locating two IoT nodes alongside a Vaisala GMP343 reference CO2 analyzer and a Met One BAM-1020 beta attenuation monitor for PM2.5 in a reference classroom for a period of four weeks. Pearson correlation coefficients between IoT and reference measurements were 0.97 for CO2 (after drift correction), 0.91 for PM2.5 (with density correction factor k = 1.42 for local aerosol composition), and 0.99 for temperature and relative humidity.

3.4 Data Analysis Methods

Descriptive statistics (mean, median, standard deviation, percentiles) were computed for all IAQ parameters stratified by season, room type, occupancy state, and time-of-day. Analysis of Variance (ANOVA) with post-hoc Tukey HSD tests was used to assess statistically significant differences between ventilation categories and seasons (significance level alpha = 0.05). Pearson and Spearman correlation analyses quantified bivariate associations between IAQ parameters and potential predictor variablesincluding outdoor temperature, wind speed, outdoor PM2.5, occupancy count (estimated from CO2 mass balance), and architectural parameters.

Multiple linear regression (MLR) and Random Forest (RF) classification models were developed to predict IAQ category (Good: CO2 < 700 ppm, Moderate: 700-1000 ppm, Poor: > 1000 ppm) from readily observable inputs. The dataset was split 70:30 for training and testing. Model performance was evaluated using accuracy, F1-score, area under the ROC curve (AUC), and mean absolute error for regression tasks. SHAP (SHapley Additive exPlanations) values were computed to interpret feature importance in the RF model.

4. RESULTS AND DISCUSSION

4.1 Overall IAQ Parameter Summary

Table 1 presents descriptive statistics for all monitored IAQ parameters aggregated across all rooms, sessions, and seasons. CO2 concentrations ranged from 415 ppm (fresh-air equivalent during unoccupied periods) to 3,847 ppm (peak during maximum occupancy in the worst-ventilated room on a calm day). The overall mean CO2 concentration during occupied hours was 1,247 ± 387 ppm, substantially exceeding the ASHRAE 62.1 threshold of 1,000 ppm. PM2.5 geometric mean was 28.4 ug/m3 (95th percentile: 89.6 ug/m3), exceeding the WHO 24-hour guideline of 15 ug/m3 in 54.2% of occupied monitoring sessions.

Table 1. Summary Statistics of IAQ Parameters Across All Monitored Rooms (N=12, 9 months)

Parameter	**Min**	**Mean**	**Median**	**Max**	**95th Pct**
CO2 (ppm)	415	1,247	1,118	3,847	2,340
PM2.5 (ug/m3)	3.2	28.4	21.7	312.8	89.6
PM10 (ug/m3)	6.1	48.9	37.3	489.4	154.2
Temperature (degC)	17.4	27.8	28.1	39.2	35.6
Rel. Humidity (%)	28.3	64.7	67.2	96.4	89.1
TVOC (ppb)	12	234	198	1,847	680
HCHO (ug/m3)	2.1	18.7	14.4	124.3	58.2

4.2 Seasonal Variation of IAQ Parameters

Significant seasonal differences were observed for all monitored parameters (one-way ANOVA, $p < 0.001$ for all). Summer season (March-May) exhibited the highest mean CO2 concentrations (1,412 ± 421 ppm) due to reduced window opening behavior associated with outdoor heat and dust. Monsoon season (June-September) showed the highest PM2.5 concentrations (mean 34.8 ug/m3) attributable to infiltration of outdoor particulates through maximally opened windows combined with resuspension of settled dust from incoming pedestrian traffic during rainfall events. Winter season (November-February) demonstrated the most favorable CO2 concentrations (mean 1,089 ± 312 ppm) corresponding to the highest window-opening frequency reported by occupants (mean 84.3% of class time).

The CO2 mass balance method estimated mean occupant-generated CO2 emission rates consistent with light sedentary activity (0.31 L/min per person), in agreement with ASHRAE metabolic rate tables. Outdoor CO2 background concentration measured by a reference node on the campus periphery averaged 427 ppm during the study period, confirming minimal influence of vehicular emissions on indoor CO2 in the afternoon measurement periods.

4.3 Influence of Ventilation Configuration

Table 2 compares IAQ parameters between single-sided and cross-ventilation room configurations. Cross-ventilated rooms demonstrated statistically significant improvements across all parameters (Welch's t-test, $p < 0.01$). The mean CO2 reduction in cross-ventilated rooms was 34.7% (from 1,389 to 907 ppm during fully occupied periods with windows fully open). PM2.5 concentrations showed a counter-intuitive increase of 18.4% in cross-ventilated rooms, attributable to enhanced outdoor air infiltration of fine particles under south-westerly wind conditions bringing campus construction dust.

Table 2. IAQ Parameters by Ventilation Configuration (Occupied Hours, All Seasons)

Parameter	Single-Sided (Mean)	Cross-Ventilated (Mean)	Difference (%)	p-value
CO2 (ppm)	1,389	907	-34.7%	< 0.001
PM2.5 (ug/m3)	24.7	29.2	+18.4%	0.003
Temperature (degC)	29.4	27.1	-7.8%	< 0.001
RH (%)	62.4	68.9	+10.4%	< 0.001
TVOC (ppb)	267	198	-25.8%	< 0.001
ACH (est.)	1.8	4.3	+138.9%	< 0.001

4.4 Effect of Window-to-Floor Ratio

A statistically significant negative linear correlation was observed between room WFR and mean occupied CO2 concentration (Pearson r = -0.78, p < 0.001, n = 12). Rooms with WFR > 0.18 maintained mean CO2 below 1000 ppm in 76.3% of occupied sessions even without supplementary ventilation, while rooms with WFR < 0.10 exceeded 1500 ppm in 61.4% of sessions. The relationship was non-linear at high occupancy densities (> 0.8 persons/m2), where even maximum window opening areas were insufficient to prevent CO2 accumulation during low-wind-speed conditions (< 1.5 m/s).

Wind speed exhibited the strongest meteorological influence on IAQ parameters (Pearson r = - 0.73 with CO2 during occupied hours). A threshold effect was identified at approximately 2.0 m/s: below this threshold, CO2 concentrations increased sharply regardless of window configuration, while above 2.0 m/s, the rate of CO2 increase with occupancy density was substantially attenuated. This finding aligns with theoretical predictions from Linden's [39] single-zone ventilation model for wind-driven conditions.

4.5 Predictive Model Performance

The Random Forest classifier achieved the highest IAQ category prediction performance (accuracy 91.3%, F1-score 0.908, AUC 0.941) on the held-out test set. The five most important input features ranked by SHAP mean absolute values were: (1) occupancy density (persons/m2), (2) outdoor wind speed (m/s),
(3) window opening area (m2), (4) outdoor PM2.5 concentration (ug/m3), and (5) indoor temperature (degC). The MLR model for continuous CO2 prediction achieved R2 = 0.81 and MAE = 124 ppm on the test set, performing adequately for coarse ventilation management applications but insufficient for precise occupant exposure assessment.

The IoT prediction system, when implemented with 15-minute moving-average inputs, reduced false alarms (predicted Poor when Good) by 62% compared to instantaneous readings, while maintaining a 94.8% detection rate for genuinely Poor IAQ episodes. This performance characteristic suggests suitability for automated window-opening alert systems integrated with building management infrastructure.

5. DISCUSSION

The findings of this study confirm and extend prior literature on classroom IAQ challenges in tropical environments. The observed mean CO2 concentration of 1,247 ppm during occupied hours is consistent with values reported by Dorizas et al. [20] in Mediterranean classrooms (1,180-1,420 ppm) andconsiderably higher than the 820 ppm reported by Stabile et al. [18] in Italian schools where mechanical extract ventilation supplemented natural infiltration. The disparity reflects both the higher occupancy densities typical of South Asian academic institutions (often 1.0-1.2 persons/m2 versus 0.4-0.6 in European studies) and the limitations of wind-driven natural ventilation under calm thermal conditions.

The identification of a critical wind speed threshold at 2.0 m/s has important implications for IAQ management strategies. Local meteorological data for the study site indicate that wind speeds fall below this threshold during approximately 38% of daytime hours annually, predominantly during pre-monsoon mornings (June-September, 07:00-10:00 IST). During these periods, which often coincide with morning lecture schedules at Indian universities, CO2 concentrations can rise from background levels to 1,500 ppm within 20-30 minutes in rooms with WFR < 0.12, consistent with rates predicted by a simple single-zone mass balance model using the measured occupancy and ventilation parameters.

The finding that cross-ventilated rooms showed significantly higher PM2.5 concentrations than single-sided rooms during certain periods highlights an important trade-off between CO2 management and particle exposure that has been inadequately addressed in existing IAQ guidelines. Current WHO and ASHRAE standards address CO2 and PM2.5 as independent parameters without explicitly acknowledging that natural ventilation strategies which improve one may worsen the other under specific outdoor air quality conditions. This trade-off suggests that a dynamic ventilation control strategy, responsive to both indoor and outdoor pollutant levels, is preferable to static window-opening recommendations.

The high AUC (0.94) achieved by the Random Forest classifier demonstrates that real-time IAQ categorization is feasible using the sensor suite implemented in this study. Deployment of such predictive systems within building management platforms could enable proactive interventions — including automated ventilation alerts, occupancy schedule adjustments, and supplementary air purifier activation
— before IAQ degrades to levels demonstrably affecting student performance. The computational overhead of the RF model is minimal (prediction latency < 5 ms on ESP32 hardware), making on-device inference feasible without cloud connectivity.

Regarding sensor performance, the field-validated IoT nodes demonstrated accuracy adequate for IAQ category determination despite operating at the lower end of the cost-performance spectrum. The primary limitation identified was PM sensor accuracy degradation at relative humidity > 80%, a condition prevalent during monsoon months. Application of a humidity correction factor (CF = 1 / (1 - RH/100) forRH < 90%) reduced PM2.5 measurement error from 24.6% to 11.3% at high humidity conditions, consistent with correction approaches recommended by Crilley et al. [40].

6. CONCLUSION

This study has demonstrated, through a rigorous nine-month field monitoring campaign using a validated IoT sensor network, that natural ventilation in small academic rooms at a South Indian university campus frequently fails to maintain indoor air quality within internationally recommended limits. The key findings are:

- CO2 concentrations exceeded 1,000 ppm during 68.4% of occupied hours in rooms with WFR < 0.12, representing unacceptable exposure conditions for approximately 2,300 students during the study period.
- Cross-ventilated rooms achieved 34.7% lower mean CO2 concentrations but 18.4% higher PM2.5 infiltration compared to single-sided ventilated rooms, highlighting a critical IAQ trade-off requiring dynamic management.
- Occupancy density (R2 = 0.87) and outdoor wind speed (R2 = 0.73) were the dominant predictors of CO2 concentration during occupied periods, with a critical wind speed threshold identified at 2.0 m/s.
- The IoT monitoring network achieved CO2 measurement accuracy within 28.4 ppm MAE after field calibration, adequate for real-time IAQ management applications.
- A Random Forest machine learning model achieved AUC = 0.941 for IAQ category prediction, enabling prospective ventilation management strategies.

Based on these findings, the following recommendations are made for institutional policymakers and building designers:

- New academic buildings in tropical climates should target WFR > 0.18 with cross-ventilation configurations oriented perpendicular to prevailing winds.
- Occupancy density in existing poorly ventilated classrooms (WFR < 0.12) should be limited to
0.5 persons/m2 during low-wind-speed periods to maintain CO2 below 1,000 ppm.
- Hybrid ventilation strategies incorporating low-energy fans or demand-controlled mechanical extract should be considered for rooms where natural ventilation alone is demonstrably inadequate.
- Continuous IoT-based IAQ monitoring should be mandated in all academic buildings as a basis for evidence-based ventilation policy, particularly during post-pandemic occupancy resumption.

Future research should extend this investigation to a larger sample of campus buildings, incorporate CFD-validated airflow simulations for parametric window design optimization, and evaluate the effectiveness of recommended interventions through controlled before-after studies. Integration of CO2-based demand-controlled natural ventilation strategies with real-time outdoor air quality data represents a promising direction for sustainable IAQ management in tropical educational buildings.

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