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Optimizing Smart Building Safety Management: A Descriptive Analytics Approach Using Microsoft Power BI and IoT Sensor Data

Muhammad Farhan Bin Hj Azmir, Mariam Mahmudah Binti Abd Aziz, Muhammad Abdul Adib Bin Abdul Aziz, Mohd Ruzaimi Bin Mohd Ariffin

Faculty of Industrial Management, Universiti Malaysia Pahang Al-Sultan Abdullah

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ABSTRACT

As the smart building paradigm establishes a global standard, ensuring occupant well-being has transitioned from a secondary utility to a fundamental safety requirement. Despite the widespread acquisition of environmental data through the Internet of Things (IoT), contemporary systems often suffer from "data overload" and fragmented silos, which obscure the longitudinal value of historical trends and result in reactive safety management. This research addresses these systemic gaps by developing a descriptive analytics dashboard using Microsoft Power BI to synthesize multi-source IoT data specifically CO_2 levels, humidity, temperature, light intensity, and motion into actionable intelligence. Adopting a project-based methodology grounded in the Software Development Life Cycle (SDLC), the study operationalizes safety thresholds derived from ASHRAE and World Health Organization (WHO) standards through an "action-driven" traffic-light categorization system. Empirical results demonstrate that monitored environmental conditions remained within "Safe" thresholds for 99.7% of the observation periods. While CO_2 (mean: 453.86 ppm) and temperature (mean: 23.52°C) remained stable within recommended ranges, light intensity was consistently observed below indoor standards. Furthermore, correlational analysis identified a direct relationship between occupant density and CO_2 fluctuations, emphasizing the necessity of integrated sensing for strategic ventilation planning. By bridging the gap between raw sensing and strategic visualization, this research provides a robust framework for transitioning smart building management from reactive maintenance to a data-driven proactive model.

INTRODUCTION

As the smart building paradigm becomes the global standard, ensuring occupant well-being has transitioned from a secondary utility to a fundamental safety requirement. Indoor Environmental Quality (IEQ) which encompass air quality, thermal comfort, and illumination. These attributes directly correlate with human health and organizational productivity. Although the Internet of Things (IoT) facilitates the large-scale acquisition of environmental data, contemporary systems often suffer from "data overload," prioritizing instantaneous alerts while overlooking the longitudinal strategic value of historical trends.

Furthermore, many building management systems operate in fragmented silos, delivering raw data that lacks the visual context essential for long-term strategic planning. This lack of integration hinders facility managers from identifying recurring risks or analyzing complex correlations, such as the impact of occupancy density on CO_2 degradation. Consequently, safety management remains largely reactive, addressing issues only after they manifest.

This study addresses these systemic gaps by developing a descriptive analytics dashboard leveraging Microsoft Power BI. By synthesizing historical IoT sensor data including CO_2 levels, humidity, and motion. This research transforms disparate raw inputs into actionable intelligence. The primary objectives include defining critical safety parameters, integrating multi-source data streams, and engineering a visualization tool that categorizes environmental conditions into "Safe," "Warning," and "Risk" thresholds. By bridging the gap between raw sensing and strategic visualization, this research provides a robust framework for data-driven decision-making, shifting smart building management toward a predictive model that ensures a healthier and more resilient environment for all occupants.

LITERATURE REVIEW

Regulatory and standards context for indoor environmental quality

Standards and guidelines for indoor environmental quality (IEQ) determine the numeric cut-points and normative categories that dashboards must present as Safe, Warning, or Critical. In the building-management literature this operationalisation frequently proceeds by mapping established reference bands (for ventilation, thermal comfort, humidity and illuminance) into dashboard thresholds and then attaching mitigation actions to each band. Several reviews and applied studies demonstrate this pattern: digital-twin and smart-building literature routinely adopt and translate standards into dashboard rules that drive visual risk states and automated recommendations (Arsiwala, Elghaish, & Zoher, 2023; Al-Ghamdi & Krarti, 2026; Casini, 2022). For example, a digital twin integrating IoT and BIM produced interactive dashboards that compared measured CO2 to normative thresholds and surfaced mitigation guidance for ventilation and HVAC adjustments (Arsiwala et al., 2023). Large reviews of DT and facility-management practice emphasise that thresholds are not purely technical but sit within lifecycle management processes where ASHRAE/WHO guidance, when available, must be reconciled with site-specific constraints and facility policies (Casini, 2022; Ghansah, 2025).

Critical operational implications emerge from two consistent findings across the literature. First, thresholds used in dashboards require careful provenance: they should be traceable to the standard (ventilation/comfort guidance) and to the assumptions used when porting them to a given building (occupant density, room volume, HVAC capacity). Digital twin reviews note that many implementations embed standard bands into status cards or gauge visuals, but they also warn that closed-loop, bi-directional control based strictly on a single standard may not yet be validated at scale (Al-Ghamdi & Krarti, 2026; Ghansah, 2025). Second, dashboards must present uncertainty and validity information alongside categorical states because IoT sensor error, calibration drift and spatial sampling introduce nontrivial uncertainty into whether a measurement truly indicates a compliance breach; edge-cloud analytics literature documents how sensor limitations and data preprocessing choices affect the reliability of threshold crossings displayed to users (Edje, Abd Latiff, & Chan, 2023). These cross-cutting messages show why dashboard risk categories should be anchored in standards but implemented with conservative logic (e.g., hysteresis, multi-sensor confirmation) and with explicit metadata about data quality and provenance (Casini, 2022; Edje et al., 2023).

Conceptual models linking environmental parameters to occupant health and safety

A coherent conceptual model for health and safety monitoring links measurable environmental variables (CO2, temperature, relative humidity, illuminance, occupancy) to mechanisms that affect health, comfort and performance. Digital twin and occupant-centric reviews place occupants at the centre of a multi-layer model where the physical environment (sensor layer), the virtual representation (DT/BIM layer), and decision processes (control/mitigation layer) interact to produce outcomes for wellbeing and operational risk (Deo et al., 2026; Al-Ghamdi & Krarti, 2026; Ghansah, 2025). These works synthesise mechanistic pathways: elevated CO2 and poor ventilation indicate reduced fresh air exchange and are proximate to cognitive and comfort complaints; temperature and humidity influence thermal stress and mould growth risk; light intensity affects visual ergonomics and alertness; occupancy both drives pollutant loading and modifies thermal loads.

Empirical and modeling studies in the matrix emphasise multi-parameter interaction rather than single-variable rules. Occupant-centric DT reviews argue that thermal comfort and cognitive outcomes are emergent properties that depend on combined thermal, air quality and lighting states and on occupant expectations and behaviour; thus, dashboards that aggregate only CO2 or only temperature risk missing joint exposures that matter for health (Deo et al., 2026). The applied digital twin example that monitored CO2 equivalent emissions used sensor fusion (BIM spatial metadata + IoT time series + ML) to predict eCO2 trends and support targeted retrofit actions, showing that multi-parameter models enable the prioritisation of interventions that reduce exposures most effectively (Arsiwala et al., 2023). Facility-management syntheses further show that predictive maintenance and fault detection combine environmental and equipment signals (e.g., HVAC runtime, vent damper position) to distinguish occupant-driven CO2 rises from system faults that require engineering responses (Casini, 2022; Ghansah, 2025).

The literature also flags confounders and context dependencies: building use (office, laboratory, classroom), occupancy schedules, room volume, and HVAC control logic substantially mediate exposure–outcome relationships. Therefore, dashboards and risk aggregation should allow stratification by room type and occupancy pattern, and should support drilldown from building-level risk metrics to room-level diagnostics so that mitigation is targeted and evidence-based (Deo et al., 2026; Arsiwala et al., 2023).

Historical vs real-time monitoring: roles and trade-offs

Descriptive, historical dashboards and real-time/predictive monitoring systems serve complementary roles in health and safety management. Reviews of DT and IoT deployments for buildings describe descriptive dashboards as valuable for trend detection, compliance auditing, and strategic maintenance planning because they consolidate accumulated records, reveal recurring problems, and enable retrospective validation of mitigation effectiveness (Ghansah, 2025; Al-Ghamdi & Krarti, 2026). Arsiwala et al. (2023) demonstrated that historical dashboards support retrofit prioritisation and carbon-equivalent monitoring by exposing long-run patterns that single-point real-time displays cannot capture. Historical analytics also facilitate regulatory reporting and stakeholder communication where evidence of persistent noncompliance or improvement trajectories is required.

In contrast, near-real-time systems enable timely alerts and operational interventions. Practical implementations combining Power BI and live pipelines have shown that near-live visualization is possible but requires robust data pipelines and edge processing to meet latency and reliability expectations; these implementations also reveal limitations such as network bottlenecks and the need for preprocessing to avoid false alarms (Schmitt et al., 2023; Edje et al., 2023). Reviews caution that the cost and complexity of fully streaming, closed-loop control (real-time sensing → automated actuation) remain substantial and that many organisations benefit most from a hybrid approach: descriptive dashboards for trend-driven planning and periodic compliance assessment, coupled with targeted real-time alerts for critical thresholds where immediate action prevents harm (Ghansah, 2025; Al-Ghamdi & Krarti, 2026).

Trade-offs therefore rest on decision latency, cost, and the risk profile of the monitored parameter. For parameters where latency matters (rapid CO_2 accumulation in small, poorly ventilated rooms or security intrusions flagged by PIR), real-time alerts are justified. For slower processes (seasonal humidity trends, long-term lighting adequacy), historical descriptive analytics provide higher value per cost and support evidence-based policy and capital planning (Arsiwala et al., 2023; Deo et al., 2026). The literature supports designing dashboards that explicitly state their operational remit (descriptive vs real-time), their data quality constraints, and the decision protocols associated with each risk band so that facility managers can apply the correct mitigation workflow.

METHODOLOGY

The methodology of this study is grounded in a project-based development approach, integrating the core principles of the Software Development Life Cycle (SDLC). The primary objective is to engineer a descriptive analytics dashboard that synthesizes disparate IoT sensor data into actionable safety insights. The research follows a five-phase structured framework, as detailed below.

Research Design Framework

This study utilizes a modified SDLC framework to ensure technical robustness and user-centric design. This framework encompasses: (1) Planning and Feasibility, (2) System Analysis and Data Profiling, (3) Design and Threshold Establishment, (4) Development and Implementation, and (5) Evaluation and Validation. This iterative process ensures that the resulting dashboard is not only technically sound but also aligned with global health and safety standards.

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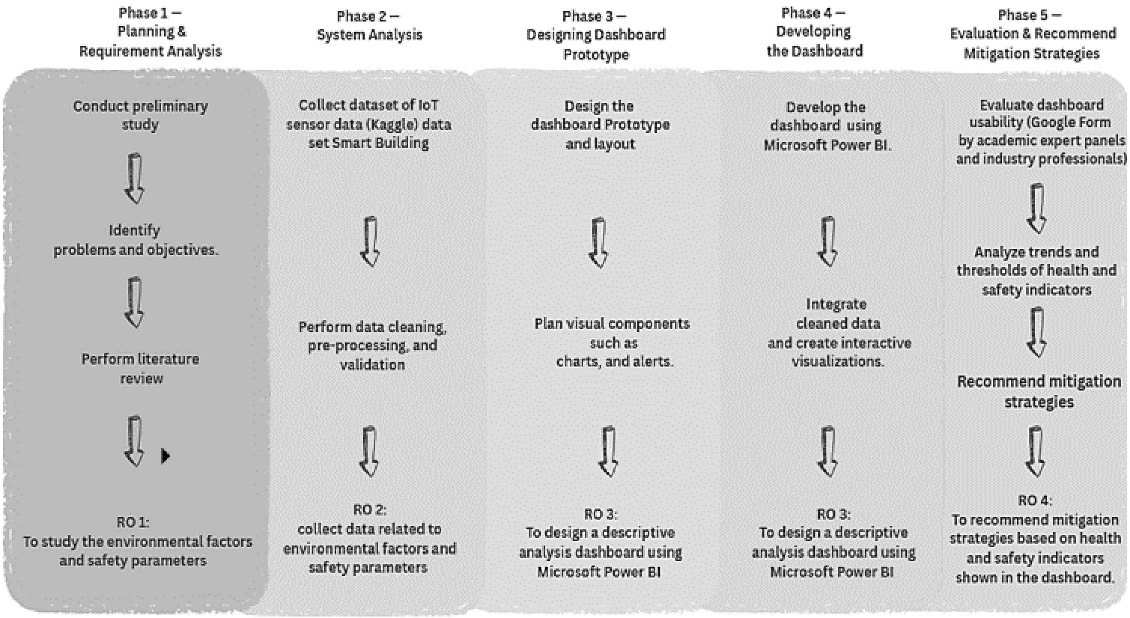

Figure 3.1: Research Design Framework Based on the SDLC Approach

Research Phases and Activities

Requirements Planning and Feasibility

The initial phase focused on identifying the critical environmental parameters necessary for monitoring occupant well-being. Based on preliminary research, five key variables were selected: CO_2 levels, temperature, humidity, Passive Infrared (PIR) motion detection, and light intensity. This phase also involved a feasibility study of Microsoft Power BI as the primary visualization engine, assessing its capability to handle complex time-series data and generate intuitive, real-time safety indicators.

System Analysis and Data Pre-processing

During this phase, a comprehensive "Smart Building IoT" dataset from Kaggle was utilized to simulate real-world building conditions. To ensure data integrity, data profiling was conducted to identify inconsistencies, outliers, and missing values.

i. Normalization: Data was cleaned via the Power Query Editor to standardize units and formats.

ii. Mapping: Environmental determinants were logically mapped to potential health risks (e.g., correlating high CO_2 with inadequate ventilation).

iii. SRS Documentation: A Software Requirements Specification (SRS) was drafted to define the dashboard architecture and technical requirements.

Dashboard Prototype and Threshold Design

A literature-driven approach was adopted to establish safety thresholds. By referencing standards from ASHRAE and the World Health Organization (WHO), specific benchmarks were defined (e.g., CO_2 >1500 ppm = Critical).

The visual architecture was designed to be "action-driven," utilizing a traffic-light color-coding system:

i. Safe (Green): Optimal conditions maintained.

ii. Warning (Yellow): Parameters approaching safety limits; monitoring required.

iii. Critical/Risk (Red): Thresholds breached; immediate mitigation required.

Table 3.1 summarizes the visual components employed to represent these metrics.

Visual Type	Description	Example Usage
Line Chart	Show trends of CO_2, temperature, humidity, and light intensity over time.	Track or observe temperature and CO_2 across days and hours to see fluctuation patterns.
Scatter Plot	Compare the relationship between two variables by analyzing how they are connected.	Compare CO_2 levels vs occupancy (motion detection or temperature vs humidity.
Filter Panel – Slicers	Time, Date/Hour, Room/Zone, Sensor Type	Allow user to filter the data dynamically
Gauge Chart	CO_2 Level vs Threshold (800 ppm)	Show current CO_2 level relative to risk threshold
Donut Chart	Percentage % Time in Safe vs Risk Zones	Visualize the proportion of safe vs risky time periods
Risk Indicator-Conditional Card / DAX Status	Color-coded "Status" (Safe / Warning / Risk) based on combined thresholds	Instant visual cue of current safety level

Development and Implementation

The dashboard was developed using Microsoft Power BI Desktop. The implementation process involved:

i. ETL Process (Extract, Transform, Load): Importing the dataset and applying Power Query transformations to filter null records and define data types.

ii. Data Modeling: Utilizing Data Analysis Expressions (DAX) to create complex measures, such as moving averages for CO_2 and dynamic risk categorization formulas.

iii. UI/UX Design: Implementing a "Report View" with a hierarchical layout—top-level KPIs for immediate awareness, followed by line charts for temporal trends, and scatter plots for correlational analysis.

iv. Interactivity: Slicers and drill-through features were added to allow building managers to filter data by specific rooms, sensor types, or timeframes.

Evaluation and Validation

The final phase involves an empirical evaluation of the dashboard's performance and utility. A panel of academic experts and industry professionals will assess the system based on its functionality and decision-support capabilities. Data collection for this evaluation is conducted via a Likert-scale questionnaire and qualitative short-answer feedback. The focus of the evaluation remains on the accuracy of the descriptive trends and the effectiveness of the visual risk indicators in supporting proactive building management.

RESULT AND DISCUSSION

Dashboard Overview

The Smart Building Health and Safety dashboard is based on the Microsoft Power BI to visualize and analyze the IoT sensor data of the Kaggle Smart Building dataset. The dashboard consolidates multiple safety related parameters into a one platform, allowing for interactive analysis and clear presentation of results. It also includes

KPI cards, gauge indicators, donut charts, scatter plots, and time-series graphs each of which identifies a particular aspect of the environment or safety. The combination of these images gives a full picture on the building environmental performance and safety status.

To ensure granular insight into indoor environmental quality, the dashboard integrates a suite of specialized visual instruments that each address specific facets of safety and performance. KPI cards and gauge indicators provide instantaneous situational awareness by highlighting current values relative to established industry safety thresholds, while donut charts offer a proportional summary of environmental compliance by visualizing the time spent within safe versus critical zones. Furthermore, scatter plots and time-series graphs are employed to perform advanced correlational and temporal analysis, allowing managers to identify how variables like occupancy density influence air quality trends and to detect recurring anomalies that may signal underlying mechanical or structural issues.

The synergy of these diverse graphical elements facilitates a holistic assessment of the building's environmental integrity, transforming disparate sensor outputs into a cohesive and actionable operational profile. By presenting complex data through an integrated and intuitive lens, the dashboard empowers facility managers and safety officers to transition from traditional reactive maintenance to a sophisticated, data-driven proactive management model. Ultimately, this approach to descriptive analytics ensures that building performance is monitored with high precision, fostering a resilient indoor environment that prioritizes the long-term health, safety, and well-being of all occupants.

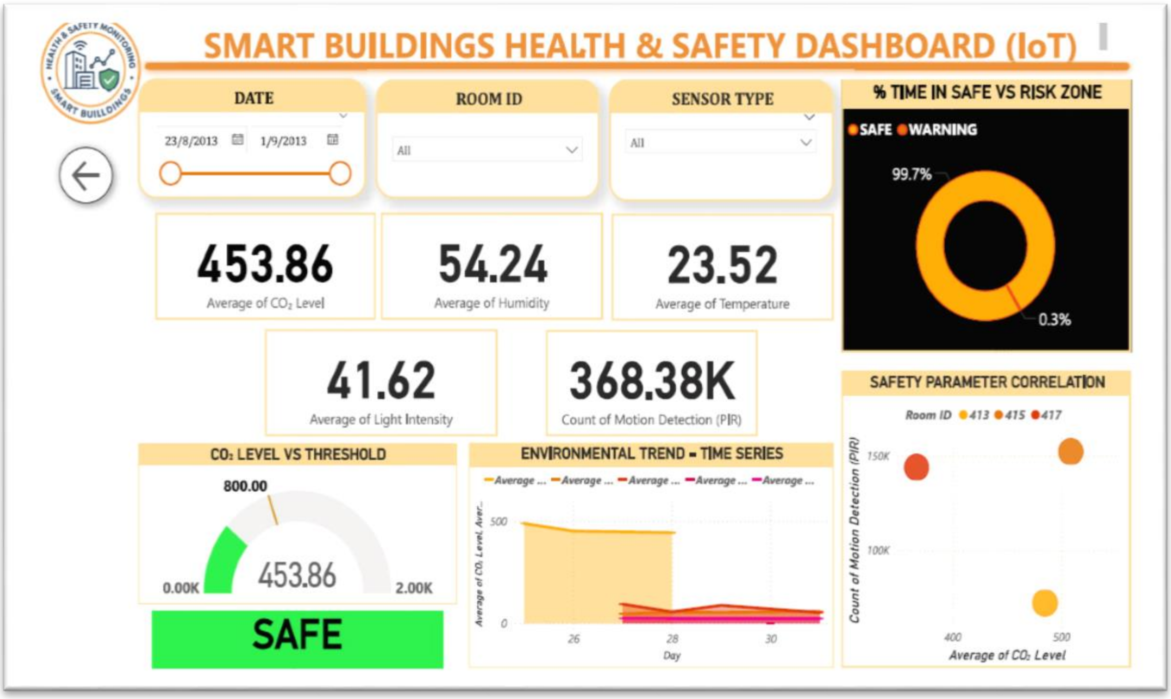

Figure 4.1: Smart Building Health & Safety Dashboard (Overall View)

Safe vs Risk Zone Analysis

To illustrate a better picture of environmental condition distribution, the dashboard also has a donut chart that identifies data in safe and risk areas according to preset threshold values. The analysis reveals that of the 100 monitored periods, 99.7% were of safe conditions and only 0.3% were of warning zones. It means that the environmental management is fairly effective in the building, and the CO_2, temperature, and humidity levels are safe. Nevertheless, such a low percentage in the warning zone demonstrates the significance of constant monitoring because even the slightest variations may change the comfort or safety of occupants when they are not taken care of.

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Figure 4.3: Percentage of Time Spent in Safe versus Risk Zones

Table 4.2: Safe vs Risk Zone Analysis

Aspect	Value	Interpretation
Safe Zone	99.7%	Conditions remained within safe limits
Warning Zone	0.3%	Minor fluctuations detected
Overall Condition	Mostly safe	Environment well-maintained
Implication	Stable parameters	Small variations require monitoring

Environmental Trend – Time Series

Time-series line chart is included in the dashboard to show the variation of environmental parameters over the period of monitoring. The measurements have shown that the CO_2 and temperature remained relatively constant with no serious changes out of the recommended limits of indoor comfort and safety. By contrast, humidity also had relative fluctuations which showed the variation of environmental factors which could be affected by the occupancy trends or ventilation trends. Temporal changes are the most critical aspects to be visualized to recognize recurring patterns and possible risk conditions.

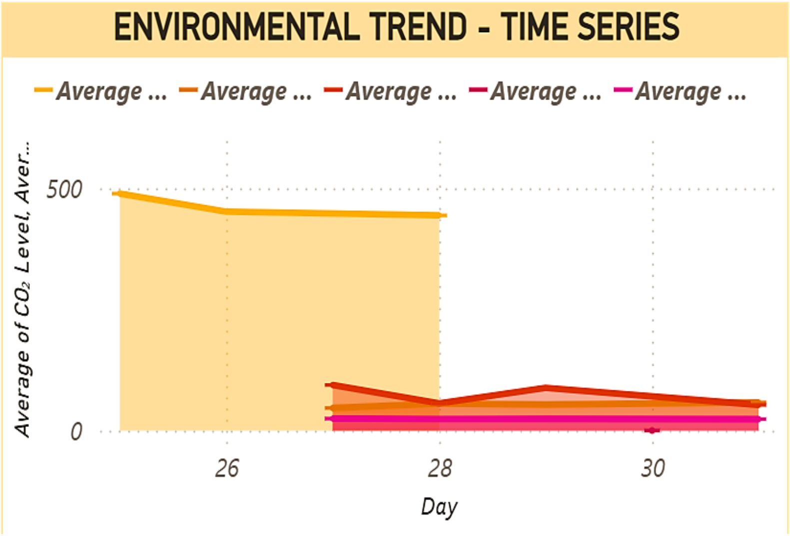

Figure 4.4: Environmental Trends in CO_2, Temperature, and Humidity Over Time

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Table 4.3: Environmental Trend – Time Series

Parameter	**Average Value**	**Observed Trend**	**Recommended Range (ASHRAE/WHO)**	**Interpretation**
CO_2 Level (ppm)	453.86 ppm	Decreased Day 25–28, then stable	< 1000 ppm (ASHRAE)	Safe; good ventilation and air circulation.
Temperature (°C)	23.52°C	Stable throughout	18–26°C (WHO/ASHRAE)	Within comfort range; no thermal issues.
Humidity (%)	54.24%	Minor fluctuations (Day 27–29)	40–60% (WHO)	Acceptable; small changes due to occupancy/ventilation.
Light Intensity (Lux)	41.62 lux	Consistently low	300–500 lux (Indoor standard)	Below recommended lighting; insufficient illumination.
Motion (PIR)	368,380 counts	Spikes on Day 27 & 29	N/A	Higher occupancy activity on certain days.

Safety Parameter Correlation

In order to further analyze the correlation between occupancy and indoor air quality, a scatter plot was created in order to test the correlation of the variables motion detection (PIR) and the CO_2 level at different room ID. The findings indicate that increased occupancy events (counts of motion) were related to a bit higher CO_2, supporting the well-established link between the fact that human presence strongly correlates with higher CO_2 amounts. Ventilation strategies in the facilitation of air quality are emphasized by this relationship, especially in high or long-occupancy spaces.

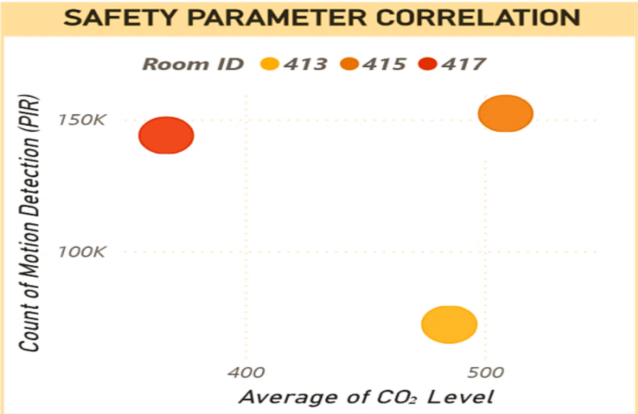

Figure 4.5: Correlation between Motion Detection (PIR) and CO_2 Levels across Rooms

Table 4.4: Safety Parameter Correlation

Room ID	**Average CO_2 Level (ppm)**	**PIR Activity (Motion Count)**	**ASHRAE Recommended CO_2 Range**	**Interpretation**
413	400 ppm	150K	< 1000 ppm	CO_2 well below ASHRAE limits; occupancy-linked increase observed.

415	450 ppm	100K	< 1000 ppm	Lower occupancy results in lower CO_2; aligns with ASHRAE.
417	500 ppm	150K	< 1000 ppm	Higher occupancy increases CO_2 slightly but still within ASHRAE range.

Evaluation Result

This section presents the evaluation results obtained from academic experts and industry professionals regarding the developed Smart Building Health and Safety Dashboard. The test was intended to determine the functionality, usability, visual design and the overall functionality of the dashboard in fulfilling the targeted goals. The questionnaire was distributed in the form of a Google Form to expert panels and the industry professionals. The feedback collected analyzed both quantitatively and qualitatively in order to determine areas where strengths and improvements were made.

Evaluation Criteria

The evaluation will be based on ten (10) major criteria, which were measured on the basis of the 5-point Likert scale (1 = Strongly Disagree, 2 = Disagree, 3 = Neutral, 4 = Agree, 5 = Strongly Agree). The criteria were crafted to assess the usability, functionality, visual effectiveness, and overall value to the Smart Building Health and Safety Dashboard in helping to monitor the environment and safety.

Table 4.5: Evaluation Criteria and Descriptions

Criteria	**Description**
Q1	Interactivity and ease of use
Q2	Layout organization and user-friendliness
Q3	Appropriateness of color coding (Safe/Warning/Risk)
Q4	Relevance of displayed parameters (CO_2, temperature, humidity, light, motion)
Q5	Effectiveness and clarity of visualizations
Q6	Usefulness for safety-related decision-making
Q7	Filtering and user control features
Q8	Achievement of monitoring objectives
Q9	Information sufficiency and readability
Q10	Open-ended feedback and improvement suggestions

CONCLUSION

This study developed and evaluated a descriptive analysis dashboard for health and safety monitoring in smart buildings using historical IoT sensor data. The project met its stated objectives by identifying key environmental and safety parameters, preparing and analysing a multi-parameter dataset, implementing an interactive Power BI dashboard prototype, and deriving mitigation strategies linked to measured indicator levels. The approach demonstrated how historical sensor records can be consolidated into actionable visual summaries that support facility-level decision-making.

Findings indicate that the monitored indoor environment remained within acceptable ranges for carbon dioxide, temperature, and humidity for the analysed period, while light levels were consistently below recommended illumination for typical indoor workspaces. Correlational analysis showed expected occupancy-driven increases in CO2, which reinforces the value of combining motion sensing with air-quality metrics for ventilation planning. The dashboard facilitated temporal trend inspection, room-level comparison, and a clear risk-status presentation that together improved situational awareness for building managers and safety officers.

The work contributes practically by delivering a usable, non-programmatic visualization tool that translates complex IoT streams into concise safety indicators and mitigation prompts. Academically, the study demonstrates the role of descriptive analytics in revealing long-term patterns that complement real-time monitoring, and it clarifies design choices for integrating multiple environmental sensors into a single decision-support interface.

Several limitations temper the conclusions and point to areas for improvement. The analysis relied on a secondary dataset rather than live sensor feeds, sensor coverage omitted key pollutants and acoustic metrics, and the evaluation sample was limited in size and stakeholder diversity. The dashboard currently implements descriptive analytics only and lacks automated alerting and predictive capability.

Future development should prioritise integration of real-time streaming, incorporation of additional pollutant and noise sensors, and deployment of predictive and anomaly-detection models to enable proactive interventions. Expanding usability testing to a broader set of end users and delivering web or mobile access will improve practical uptake. Together, these extensions will strengthen the dashboard's operational value for sustained health and safety management in smart buildings.

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