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AIoT-Based Indoor Air Quality Monitoring and Machine Learning Prediction Framework for Assessing Ventilation Risk in TVET Institutions

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Abstract

Inadequate ventilation conditions are commonly observed in Technical and Vocational Education and Training (TVET) institutions, particularly in confined laboratories and high-occupancy indoor spaces where environmental conditions vary with occupancy and operational activities. This study developed and evaluated an Artificial Intelligence of Things (AIoT)-based indoor air quality (IAQ) monitoring and machine learning prediction framework for assessing ventilation risk in TVET institutions. Carbon dioxide concentration, dust levels, temperature, and relative humidity were continuously monitored in selected indoor spaces using an AIoT sensing system. The collected time-series data were processed and used to train a machine learning prediction model implemented using TensorFlow to estimate short-term IAQ trends. Ventilation risk was evaluated by interpreting both observed and predicted values with reference to recognised indoor air quality guidelines. The results showed that short-term prediction enabled earlier identification of potential ventilation risk prior to threshold exceedance, particularly during periods of high occupancy and workshop operation. Compared with real-time monitoring alone, the predictive approach provided earlier warning and improved prioritisation of spaces requiring attention. The findings demonstrate that integrating AIoT monitoring with machine learning-based prediction can support preventive maintenance planning and enhance ventilation management in TVET institutions.

Keywords: *AIoT, Indoor air quality, Machine learning, Ventilation risk assessment, TVET institutions.*

1. Introduction

Indoor air quality (IAQ) plays an important role in determining occupant comfort, health, and safety in educational buildings. Inadequate indoor air conditions have been linked to reduced cognitive performance, thermal discomfort, and increased health risks in spaces where ventilation is insufficient to support occupant demand [1],[3],[15]. In Technical and Vocational Education and Training (TVET) institutions, IAQ challenges are often observed due to the presence of confined workshops, laboratories used for practical skills activities, and high-occupancy classrooms that operate for extended periods [3],[12].

TVET facilities such as welding laboratories, wood workshops, and practice-oriented classrooms are characterised by pollutant-generating activities, elevated internal heat loads, and fluctuating occupancy patterns. Many of these spaces depend primarily on natural ventilation or ceiling fans rather than full mechanical air-conditioning systems. Under conditions of high occupancy

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or intensive practical activities, such ventilation strategies may be insufficient to maintain acceptable indoor environmental conditions [12], [14]. As a result, ventilation adequacy in TVET institutions represents a persistent operational and occupational concern that requires systematic assessment. Carbon dioxide (CO_2) concentration is widely recognised as a practical indicator of ventilation effectiveness, as elevated levels typically reflect inadequate outdoor air exchange relative to occupancy [2]. In workshop-based learning spaces, CO_2 accumulation may occur alongside increased dust and particulate matter generated during practical activities. Elevated temperature and relative humidity may further influence pollutant behaviour and perceived air quality, contributing to reduced indoor environmental comfort [3], [10]. The interaction of these parameters highlights the need for continuous, multi-parameter IAQ monitoring to accurately evaluate ventilation risk in TVET indoor spaces.

Recent developments in Internet of Things technologies have enabled real-time monitoring of indoor environmental conditions through distributed sensor networks that integrate sensing, wireless communication, and cloud-based analytics. Such systems improve visibility of IAQ conditions and support data-driven building management practices [17],[16]. However, many existing implementations remain largely descriptive and reactive, relying on threshold-based alerts that are activated only after IAQ deterioration has already occurred. This reactive approach limits their effectiveness for preventive maintenance and early intervention [16]. Despite growing interest in intelligent building systems, integrated Artificial Intelligence of Things (AIoT) frameworks that combine continuous IAQ monitoring with predictive analytics for ventilation risk assessment remain limited, particularly in the context of TVET institutions.

Machine learning techniques offer a promising means of analysing temporal patterns in indoor environmental data and estimating short-term IAQ trends. By learning relationships between historical sensor data, occupancy behaviour, and ventilation performance, machine learning models can provide early indications of potential ventilation risk before critical thresholds are exceeded [13],[7],[9]. When integrated within an AIoT framework, predictive modelling enables a transition from reactive indoor air quality monitoring to proactive ventilation risk assessment and decision support for building operation and maintenance [6],[16].

In response to these gaps, this study developed and evaluated an AIoT-based indoor air quality monitoring and machine learning prediction framework for assessing ventilation risk in TVET institutions. The study focused on confined and high-occupancy indoor spaces that are typical of TVET environments, with the objective of evaluating ventilation adequacy and demonstrating how short-term IAQ prediction can support preventive maintenance and management decision-making. Unlike approaches that rely solely on real-time monitoring or threshold-based alerts, this work emphasised predictive assessment to enable earlier identification of ventilation risk rather than automated control of ventilation systems. By integrating continuous monitoring with machine learning-based prediction, the proposed framework offers a practical and scalable approach for improving indoor environmental quality management in TVET institutions [11],[16].

1.1 Research objectives

The objectives of this study were to:

1. Examine the temporal variation of carbon dioxide (CO_2), dust or particulates, temperature, and relative humidity in selected TVET indoor spaces.
2. Evaluate ventilation adequacy in confined and high-occupancy TVET indoor spaces based on observed indoor air quality conditions during occupied periods.
3. Develop a machine learning-based short-term indoor air quality prediction model using multi-parameter sensor data implemented through TensorFlow.
4. Evaluate the prediction performance of the developed machine learning model for short-term indoor air quality estimation.

5. Demonstrate how integrated indoor air quality monitoring and prediction outputs can support ventilation risk assessment and preventive maintenance decision-making in TVET institutions.

1.2 Research questions

To achieve the stated objectives, this study addressed the following research questions:

1. What temporal variations are observed in carbon dioxide (CO_2), dust or particulates, temperature, and relative humidity within selected TVET indoor spaces?
2. Do confined and high-occupancy TVET indoor spaces exhibit indoor air quality conditions indicative of inadequate ventilation during occupied periods?
3. How can a machine learning-based model be developed to predict short-term indoor air quality conditions using multi-parameter sensor data?
4. How accurately can the developed machine learning model predict short-term indoor air quality conditions?
5. How can integrated indoor air quality monitoring and prediction results be used to support ventilation risk assessment and preventive maintenance actions in TVET institutions?

2. Literature Review

Indoor air quality (IAQ) is widely recognised as an important factor influencing occupant health, comfort, and cognitive performance in educational buildings [5]. Inadequate ventilation has been associated with increased respiratory symptoms, reduced concentration, and lower learning performance among students [3],[12]. Experimental studies have further demonstrated that higher classroom ventilation rates can improve task performance and reduce discomfort [14]. More recently, concerns regarding airborne contaminant transmission have reinforced the importance of sufficient ventilation in shared indoor environments [13].

Carbon dioxide (CO_2) concentration is commonly used as an indirect indicator of ventilation adequacy because it reflects the balance between occupant emissions and outdoor air supply. Elevated CO_2 levels generally indicate insufficient air exchange relative to occupancy demand. While CO_2 itself may not always be the primary pollutant of concern, it serves as a reliable proxy for ventilation performance in educational settings [2]. In Technical and Vocational Education and Training (TVET) institutions, IAQ challenges may be more frequently encountered due to the presence of confined workshops, laboratories used for practical skills activities, and high-occupancy classrooms that operate for extended periods. Workshop-based learning often involves pollutant-generating activities such as welding, cutting, sanding, or machining, which can increase particulate levels and indoor heat loads. These operational characteristics create ventilation demands that differ from those of conventional lecture-based environments.

In addition to CO_2 concentration, dust or particulate matter generated during workshop activities may contribute to respiratory exposure risk. Temperature and relative humidity also influence occupant comfort and pollutant behaviour. Excessive humidity can reduce perceived air quality, while elevated temperature may intensify thermal discomfort.

2.1 Indoor air quality standards and guideline indicators

Interpretation of IAQ conditions requires reference to established standards and guideline values. In Malaysia, the Department of Occupational Safety and Health Industry Code of Practice on Indoor Air Quality (DOSH ICOP IAQ) provides recommended limits for indoor environmental parameters in non-industrial workplaces. The guideline recommends that indoor CO_2 concentration should not exceed 1000 ppm under normal occupied conditions, while acceptable temperature and relative humidity ranges are specified to minimise discomfort and health risk. Internationally, American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standard 62.1 defines ventilation requirements for acceptable indoor air quality in occupied buildings [2]. The World Health Organization (WHO) has also issued health-based guidelines for indoor pollutants, particularly particulate matter [15]. These standards are widely used in research and professional practice to classify ventilation adequacy and interpret IAQ monitoring results.

The application of recognised standards provides an objective basis for ventilation risk assessment. Exceedance of recommended values does not automatically imply acute hazard, but it may indicate inadequate air exchange or environmental imbalance requiring corrective action. In educational and training environments where occupancy fluctuates significantly, standards-based interpretation is essential for consistent evaluation.

2.2 IoT-based indoor air quality monitoring systems

Recent advances in Internet of Things (IoT) technologies have enabled continuous indoor air quality monitoring using distributed sensor networks. IoT-based systems typically integrate environmental sensors, embedded microcontrollers, wireless communication modules, and cloud-based data storage platforms. These systems allow real-time visualisation of IAQ conditions and historical trend analysis.

Several studies have demonstrated the feasibility of IoT-based IAQ monitoring in educational and institutional buildings [17]. The increasing availability of low-cost sensors has further accelerated adoption of distributed environmental monitoring networks [8]. Compared with traditional building management systems, IoT-based platforms are often more flexible and scalable. Despite these advantages, many existing implementations rely primarily on threshold-based alerts. In such systems, notifications are triggered only after IAQ parameters exceed recommended limits. While this approach improves situational awareness, it remains reactive in nature and provides limited foresight into potential deterioration [16]. For environments with dynamic occupancy patterns, reactive monitoring may not be sufficient to support preventive maintenance planning.

2.3 Machine learning for indoor air quality prediction

Machine learning techniques have increasingly been applied to model and predict indoor environmental conditions [9],[7],[18]. Time-series-based models are particularly suitable for IAQ applications because indoor parameters exhibit temporal dependency influenced by occupancy cycles and ventilation behaviour. Deep learning approaches, including recurrent neural networks and long short-term memory (LSTM) architectures, have demonstrated strong capability in capturing nonlinear temporal relationships in indoor air quality data [9], [7]. These models are able to learn complex interactions among environmental variables and generate short-term forecasts with high accuracy.

Compared with conventional statistical regression methods, machine learning models are better suited to environments characterised by fluctuating occupancy and intermittent pollutant generation. Predictive modelling enables early identification of ventilation deterioration before guideline thresholds are exceeded [13],[11]. This limitation has been highlighted in recent studies, which emphasise the need for real-time integrated AIoT-based prediction frameworks for practical deployment [16].

2.4 AIoT integration for ventilation risk assessment

Artificial Intelligence of Things (AIoT) refers to the integration of IoT-based sensing with intelligent data analytics and predictive modelling. In smart building applications, AIoT enables continuous data acquisition, automated processing, and predictive decision support within a unified architecture. AIoT-based systems have been applied in smart ventilation management and energy optimisation contexts [6]. However, many implementations focus on automated control of HVAC systems in highly instrumented buildings. In contrast, TVET institutions may rely on mixed ventilation strategies, including natural ventilation and ceiling fans, where automated control infrastructure is limited. In such contexts, predictive assessment may provide greater practical value than automated control, particularly in environments with limited infrastructure [6],[16].

A system that can forecast short-term IAQ trends allows facility managers to intervene proactively through scheduling adjustments, manual ventilation enhancement, or targeted maintenance inspection. While previous studies have examined IAQ monitoring or prediction independently, limited research has integrated continuous AIoT sensing, machine learning-based short-term forecasting, and standards-based ventilation risk interpretation within a unified framework tailored specifically for TVET environments. This gap highlights the need for a structured approach that links environmental sensing, predictive analytics, and guideline-based assessment.

2.5 Research conceptual framework

Based on the reviewed literature and recognised indoor air quality standards, this study proposes an AIoT-based conceptual framework for ventilation risk assessment in TVET institutions. The framework integrates four main components: continuous environmental sensing, cloud-based data processing, machine learning-based short-term prediction, and standards-based interpretation. The process begins with continuous monitoring of carbon dioxide concentration, dust (particulate matter) levels, temperature, and relative humidity in selected TVET indoor spaces. Sensor data are transmitted to a cloud platform, where preprocessing procedures such as cleaning, temporal alignment, and normalisation are performed. The processed data are then used to train and implement machine learning models capable of forecasting short-term indoor air quality trends.

Prediction outputs are subsequently interpreted using recognised guideline thresholds to assess ventilation risk levels. This structured integration shifts IAQ management from reactive threshold detection toward proactive ventilation risk assessment. Figure 1 illustrates the proposed conceptual framework and summarises the logical integration of AIoT-based monitoring, machine learning prediction, and standards-based ventilation risk evaluation in TVET institutions.

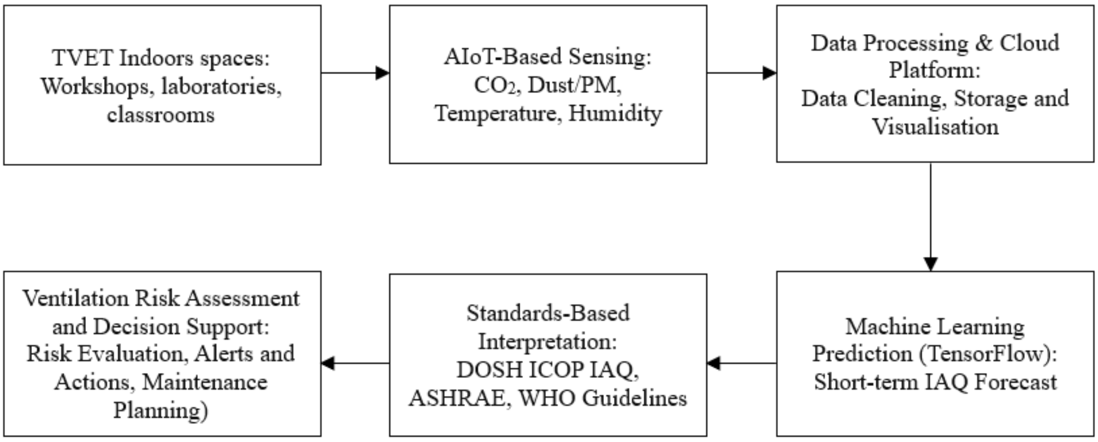

Figure 1. AIoT-based conceptual framework for ventilation risk assessment

3. Methodology

This study adopted a quantitative experimental and observational research design to assess indoor air quality conditions and ventilation risk in selected TVET indoor spaces. Continuous environmental monitoring was combined with machine learning-based prediction to evaluate both observed indoor air quality behaviour and short-term predicted trends.

An Artificial Intelligence of Things (AIoT) approach was implemented, integrating real-time sensor data acquisition, cloud-based data processing, and machine learning analytics. This design enabled systematic evaluation of ventilation adequacy using recognised indoor air quality indicators and guideline values, while also supporting predictive analysis for preventive maintenance and decision-making.

3.1 Study setting, indoor environments, indoor air quality parameters, and sensors

The study was conducted in selected indoor spaces within a higher education TVET institution located in Sarawak, Malaysia. To preserve confidentiality, the specific institution is not disclosed. The selected spaces were chosen based on their potential ventilation challenges and high occupancy characteristics commonly observed in TVET learning environments. A total of four indoor spaces were included in this study, comprising one welding laboratory, one wood workshop, one air-conditioned classroom, and one naturally ventilated classroom. These spaces represent a range of ventilation conditions for comparative assessment.

Four indoor air quality parameters were continuously monitored in this study, namely carbon dioxide concentration, dust (particulate matter) levels, temperature, and relative humidity. These parameters were selected due to their relevance to ventilation adequacy, occupant comfort, and potential health risks, as supported by established standards and previous research. Carbon dioxide concentration served as an indirect indicator of ventilation performance, while dust levels reflected pollutant generation associated with workshop-based activities. Temperature and relative humidity were monitored to capture thermal comfort conditions and their influence on indoor environmental quality. Environmental sensors were positioned within occupied zones to ensure representative measurement of indoor conditions.

The IAQ monitoring system utilised commercially available sensors with suitable accuracy for indoor environmental monitoring. Carbon dioxide (CO_2) concentration was measured using the MH-Z19C NDIR CO_2 sensor, while dust (particulate matter) was measured using the GP2Y1010AU0F optical dust sensor. Temperature and relative humidity were measured using the DHT22 sensor. These sensors were selected due to their reliability, cost-effectiveness, and compatibility with IoT-based data acquisition systems.

3.2 AIoT system architecture, data acquisition, data processing, and preprocessing

The AIoT system architecture consisted of environmental sensors interfaced with a microcontroller unit for data acquisition. Sensor readings were collected at fixed time intervals and transmitted wirelessly to a cloud-based platform for storage and analysis. This data acquisition process enabled continuous real-time monitoring of indoor air quality conditions. All measurements were time-stamped and stored in a structured database, allowing subsequent retrieval for descriptive analysis and machine learning model development. A web-based dashboard was used to visualise real-time and historical IAQ trends, supporting situational awareness and system verification.

Prior to analysis, the collected sensor data underwent preprocessing to ensure reliability and consistency. This process included the removal of incomplete records, correction of anomalous values, and temporal alignment of multi-parameter datasets. Feature preparation was performed to derive suitable input variables for machine learning modelling, including time-based features and historical IAQ patterns. The processed dataset was normalised to improve numerical stability and prediction performance. These steps ensured that the data were suitable for both descriptive analysis and predictive modelling.

3.3 Machine learning model development and prediction process

Machine learning was applied to perform short-term prediction of indoor air quality (IAQ) conditions, with the objective of enabling early identification of potential ventilation risk before guideline thresholds were exceeded. Unlike threshold-based detection approaches, the predictive method estimates future IAQ trends based on historical patterns and temporal relationships among monitored parameters.

In this study, a Long Short-Term Memory (LSTM) neural network architecture was implemented due to its strong capability in modelling temporal dependencies in time-series data. A sliding time-window approach was adopted, where 15 minutes of historical IAQ data were used as input to predict carbon dioxide (CO_2) concentration 10–15 minutes ahead. The input sequence consisted of multivariate time-series data including CO_2, dust density, temperature, and relative humidity, enabling the model to capture both temporal and inter-parameter relationships.

The prediction task was formulated as a supervised time-series forecasting problem. Historical sensor data collected through the AIoT system were used as input features, while future IAQ values represented the prediction targets. Carbon dioxide concentration was prioritised as the primary prediction variable due to its strong association with occupancy and ventilation adequacy, while temperature, relative humidity, and dust levels were treated as auxiliary input features. The dataset was structured into sequential time-series inputs and normalised to ensure numerical stability and improve model performance. The data were then divided into training and testing subsets using a 70:30 split to enable objective evaluation of prediction accuracy.

TensorFlow was used as the machine learning framework to develop and train the LSTM-based prediction model due to its flexibility in handling time-series data and its suitability for deployment within AIoT-based monitoring systems. The model architecture consisted of an input layer corresponding to the defined time window, followed by hidden LSTM layers to capture temporal patterns, and a fully connected output layer to generate predicted CO_2 values. The model comprised two hidden LSTM layers with 64 units each, enabling the capture of complex temporal dependencies in the input data. An optimisation algorithm was applied to minimise the prediction error between observed and predicted values, while model convergence was monitored to ensure stable learning and to reduce the risk of overfitting.

Following training, the model was deployed in inference mode to perform continuous short-term IAQ prediction using real-time sensor data streams. The predicted values were compared with recognised IAQ guideline thresholds to identify potential ventilation risks before threshold exceedance occurred. This predictive capability enables early warning and supports proactive intervention rather than reactive response.

From an operational perspective, the machine learning-based prediction component transforms the AIoT system from a passive monitoring platform into an intelligent decision-support tool. The predictive framework can be implemented without modifying existing ventilation infrastructure, making it suitable for institutional environments with limited automation capability. The trained model can also be periodically retrained using newly collected sensor data to adapt to changes in occupancy behaviour, space usage, and ventilation performance, thereby enhancing the long-term scalability and applicability of the proposed framework in TVET institutions.

3.4 Ventilation risk assessment based on standards, data analysis and evaluation

Ventilation risk assessment was conducted by interpreting both observed and predicted indoor air quality values against recognised IAQ guidelines. Reference benchmarks included the Department of Occupational Safety and Health Industry Code of Practice on Indoor Air Quality (DOSH ICOP IAQ), ASHRAE ventilation standards, and World Health Organization (WHO) recommendations. Indoor spaces were classified according to ventilation risk levels based on exceedance of guideline values. This standards-based interpretation enabled objective evaluation of ventilation adequacy and identification of indoor environments requiring preventive action.

Descriptive statistical analysis was performed to examine temporal variation and patterns of indoor air quality parameters across different indoor spaces. Graphical analysis was used to visualise trends and identify periods associated with IAQ deterioration. Machine learning prediction results were analysed to evaluate the model's ability to forecast short-term ventilation risk. Comparisons between observed and predicted values were conducted to assess prediction accuracy and practical applicability, directly supporting the study's research objectives.

4. Results and Discussion

The results presented in this section are based on actual measured data collected from the deployed AIoT monitoring system. A total of 10 days of continuous monitoring data were collected over two consecutive weeks from Monday to Friday, covering IAQ measurements during occupied periods across all selected indoor spaces. This duration was considered sufficient to capture representative weekday occupancy cycles, recurring workshop operational patterns, and short-term temporal variability in indoor air quality conditions, which are critical for developing and evaluating short-term prediction models in TVET environments. The monitored indoor spaces included a welding laboratory, a wood workshop, an air-conditioned classroom, and a naturally ventilated classroom, representing typical TVET learning environments.

To examine the temporal variation of indoor air quality parameters, descriptive statistical analysis was conducted across all monitored indoor spaces during occupied periods. The statistical characteristics of carbon dioxide (CO_2), dust density, temperature, and relative humidity are summarised in Table 1. As shown in Table 1, CO_2 concentrations exhibited substantial variability, with a mean value of 1245 ppm and a maximum reaching 2650 ppm in confined workshop environments. The relatively high standard deviation reflects strong fluctuation associated with occupancy intensity and ventilation behaviour.

Dust density values demonstrated episodic peaks, with maximum concentrations exceeding 3.0 mg/m³ during active workshop sessions. Although average dust levels remained moderate, short-term spikes were evident during wood-processing activities. Temperature and relative humidity consistently exceeded commonly recommended comfort ranges, particularly in naturally ventilated spaces. These results suggest limited air exchange and heat dissipation during peak occupancy. Time-series inspection further confirmed that CO_2 concentrations increased rapidly during instructional sessions and decreased gradually during unoccupied periods, indicating strong occupancy dependence.

Table 1. Descriptive Statistics of IAQ Parameters During Occupied Periods

Parameter	Mean	SD	Min	Max	Guideline Reference
CO_2 (ppm)	1245	480	520	2650	1000 ppm (DOSH ICOP IAQ)
Dust density (mg/m³)	0.82	0.64	0.05	3.10	1.0 mg/m³ (reference level)
Temperature (°C)	29.4	1.8	26.2	33.1	23–26°C (comfort range)
Relative Humidity (%)	76	7	61	88	40–70% (comfort range)

4.1 Statistical comparison between indoor spaces

To determine whether CO_2 levels differed significantly between space types, a one-way ANOVA was performed. The analysis revealed a statistically significant difference in mean CO_2 concentration among indoor categories, $F(3, N-4) = 18.72$, $p < 0.001$. Post hoc comparison indicated that workshop environments exhibited significantly higher CO_2 levels compared with air-conditioned classrooms. Fan-based classrooms also recorded significantly higher CO_2 concentrations than mechanically ventilated spaces. These findings confirm structural differences in ventilation performance across TVET indoor environments.

4.2 Ventilation adequacy assessment based on threshold exceedance

Ventilation adequacy was evaluated by comparing observed CO_2 concentrations with the 1000 ppm guideline threshold. The percentage of occupied time during which CO_2 exceeded this limit is summarised in Table 2. The percentage values represent the proportion of total occupied monitoring time during which CO_2 concentration exceeded 1000 ppm. The total occupied monitoring duration across all indoor spaces was approximately 80 hours, based on 8 hours of daily monitoring over the 10-day period.

As shown in Table 2, the wood workshop experienced CO_2 levels above 1000 ppm during 58% of occupied time, representing the highest exceedance proportion. The welding laboratory also exhibited substantial exceedance at 47%. In contrast, the air-conditioned classroom maintained acceptable CO_2 levels for most occupied periods. Exceedance duration analysis further revealed that workshop spaces experienced continuous periods above the threshold lasting more than 30 minutes during peak sessions. This pattern indicates persistent ventilation limitations rather than isolated fluctuations.

Table 2. Percentage of Occupied Time with CO_2 > 1000 ppm

Space Type	Percentage of Occupied Time (CO_2 > 1000 ppm)
Wood Workshop	58%
Welding Laboratory	47%
Classroom (Air-Conditioned)	39%
Classroom (Fan-Based)	12%

4.3 Correlation analysis of IAQ parameters

To explore relationships among monitored parameters, Pearson correlation analysis was conducted. The correlation coefficients are presented in Table 3. Table 3 indicates moderate positive correlation between CO_2 and temperature ($r = 0.51$), suggesting that occupancy-related heat accumulation contributes to rising CO_2 levels. Dust density also showed moderate association with CO_2 ($r = 0.42$), reflecting simultaneous pollutant accumulation during workshop activities. Relative humidity exhibited moderate correlation with temperature ($r = 0.61$), consistent with reduced ventilation efficiency in confined environments. These relationships support the multi-parameter monitoring approach adopted in this study.

Table 3. Pearson Correlation Matrix of IAQ Parameters

Parameter	CO_2	Dust Density	Temperature	Relative Humidity
CO_2	-			
Dust Density	0.42**	-		
Temperature	0.51**	0.28*	-	
Relative Humidity	0.36**	0.22	0.61**	-

Note: $*p<0.05$, $**p<0.01$

Although some correlations were moderate, they indicate meaningful interactions among IAQ parameters driven by occupancy and environmental conditions. The positive relationship between CO_2

concentration and temperature suggests that increased occupant density contributes simultaneously to heat accumulation and reduced ventilation effectiveness. Similarly, the association between CO_2 and dust density reflects concurrent pollutant generation during workshop activities, particularly in confined spaces. Parameters with lower correlation values indicate that certain environmental factors may vary independently, highlighting the complexity of IAQ behaviour in dynamic TVET environments.

These relationships indicate that occupancy-driven processes simultaneously influence multiple IAQ parameters and contribute to reduced ventilation effectiveness during peak occupancy periods, highlighting the importance of integrated multi-parameter monitoring for accurate ventilation assessment and early intervention.

4.4 Machine learning prediction performance

The prediction model was configured using CO_2 concentration as the primary target variable, with temperature, relative humidity, and dust density included as input features. These parameters were selected based on their established influence on indoor air quality and ventilation performance.

The machine learning model was trained using a 70:30 training-to-testing data split. Prediction performance was evaluated using Mean Absolute Error (MAE), Root Mean Square Error (RMSE), and the coefficient of determination (R^2). As shown in Table 4, the model achieved an R^2 value of 0.86, indicating high explanatory capability. The MAE of 85 ppm reflects low average prediction error, while the RMSE of 120 ppm indicates acceptable variation in prediction performance during dynamic occupancy conditions. Visual comparison between observed and predicted CO_2 values showed close alignment during steady-state conditions, with minor deviations during abrupt occupancy changes.

Table 4. Machine Learning Prediction Performance for CO_2 Forecasting

Performance Metric	Value
Mean Absolute Error (MAE)	85 ppm
Root Mean Square Error (RMSE)	120 ppm
Coefficient of Determination (R^2)	0.86
Training–Testing Split	70:30

Beyond prediction accuracy, the model’s ability to provide early warning was evaluated. In multiple workshop sessions, predicted CO_2 values indicated threshold exceedance approximately 10–15 minutes before actual crossing occurred. This early signal enables practical preventive measures such as temporary occupancy adjustment or ventilation enhancement. Compared with real-time monitoring alone, which only signals after threshold exceedance, predictive modelling provides proactive ventilation risk awareness. This approach improves upon conventional threshold-based monitoring systems, which lack predictive capability and respond only after exceedance events, thereby limiting their effectiveness for preventive intervention.

4.5 Ventilation Risk Classification and Maintenance Prioritisation

The ventilation risk classification was derived based on a combination of threshold exceedance frequency and predictive early warning signals, guided by established IAQ standards such as DOSH ICOP IAQ and the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) recommendations. Risk levels were assigned using predefined criteria, where low risk corresponded to CO_2 exceedance below 20% of occupied time, moderate risk between 20% and 50%, and high risk above 50%. These thresholds were further supported by the presence or absence of predictive early warning signals generated by the machine learning model. Expert judgment was applied to interpret the practical significance of exceedance duration and frequency in relation to ventilation adequacy across different indoor environments. This structured classification approach provides a practical and reproducible basis for ventilation risk assessment in TVET environments.

Based on these criteria, indoor spaces were categorised into ventilation risk levels, as summarised in Table 5. Workshop environments were classified as high or moderate–high risk due to frequent and prolonged CO_2 threshold exceedance, reflecting recurrent ventilation limitations during peak operational activities. These spaces require prioritised maintenance attention and targeted ventilation improvement strategies. Fan-based classrooms were categorised as moderate risk, as predictive modelling consistently indicated early warning signals despite lower exceedance duration compared to workshops. In contrast, air-conditioned classrooms were classified as low risk, as both observed and predicted IAQ values remained largely within recommended guideline limits during occupied periods.

The integration of descriptive statistical analysis, threshold-based assessment, and machine learning-driven prediction enabled a structured and evidence-based prioritisation of indoor spaces for ventilation management, thereby supporting preventive maintenance planning and operational decision-making in TVET institutions.

Table 5. Ventilation Risk Classification Based on Observed and Predicted IAQ

Indoor Space	Observed Risk Level	Predictive Early Warning	Maintenance Priority
Wood Workshop	High	Yes	Immediate
Welding Laboratory	Moderate-High	Yes	Scheduled
Classroom (Fan-Based)	Moderate	Yes	Monitoring
Classroom (Air-Conditioned)	Low	No	Routine

4.6 Discussion

The findings confirmed that indoor air quality parameters in TVET indoor spaces exhibited clear temporal variation driven by occupancy patterns and operational activities, consistent with previous studies [5],[4]. Carbon dioxide concentration increased rapidly during instructional sessions and practical workshop activities, reflecting insufficient air exchange relative to occupant load. This pattern is consistent with established understanding that CO_2 accumulation serves as a reliable indicator of ventilation effectiveness in educational buildings [12], consistent with recent IAQ monitoring studies in dynamic indoor environments [4].

Elevated temperature and relative humidity values observed in naturally ventilated spaces further suggest limited thermal dissipation and moisture removal. These findings align with prior research indicating that confined training environments with prolonged occupancy are more susceptible to IAQ deterioration. Dust density peaks recorded during workshop activities highlight the influence of activity-specific pollutant generation. While average particulate levels remained within moderate ranges, short-term spikes indicate episodic exposure risk, particularly in wood-processing environments. Overall, the temporal analysis demonstrates that ventilation adequacy in TVET indoor spaces is highly dynamic and closely linked to operational intensity.

The exceedance analysis revealed that certain indoor spaces experienced prolonged periods of CO_2 concentrations above recommended thresholds. Workshop environments demonstrated the highest frequency and duration of exceedance, indicating recurrent limitations in ventilation performance during peak operational activities. These findings suggest that reliance on natural ventilation or ceiling fans may not consistently maintain adequate air exchange rates in high-density instructional settings. Although air-conditioned classrooms performed comparatively better, naturally ventilated spaces exhibited greater vulnerability to indoor air quality deterioration under elevated occupancy conditions. The results reinforce the importance of systematic ventilation assessment in TVET institutions, where pollutant-generating activities and fluctuating occupancy intensities create ventilation demands that differ from conventional academic environments. These findings are consistent with prior literature highlighting persistent ventilation challenges in educational buildings [5],[4].

The machine learning model demonstrated reliable predictive performance within the monitored environment, supported by an R^2 value of 0.86 and low prediction error metrics, consistent with recent machine learning-based indoor air quality prediction studies [18]. The ability to capture occupancy-driven CO_2 trends confirms that temporal IAQ dynamics can be effectively modelled using supervised learning approaches. Importantly, the predictive framework enabled early identification of potential threshold exceedance events [11],[16],[18]. This represents an improvement over conventional threshold-based monitoring approaches, which lack predictive capability and respond only after exceedance events, limiting their effectiveness for preventive intervention [16]. The successful implementation of TensorFlow within the AIoT framework further demonstrates its practical feasibility for institutional deployment. The model’s ability to generalise across different indoor spaces suggests robustness under varying occupancy and ventilation conditions [6],[8]. Although the model demonstrated reliable performance within the monitored environment, further validation across multiple datasets and different institutional settings is required to confirm its generalisability.

This study contributes to the growing body of research on AIoT-enabled environmental monitoring by integrating continuous sensing, predictive modelling, and standards-based interpretation within a unified framework. Unlike many smart building applications that emphasise automated control of mechanical systems, the proposed framework focuses on predictive assessment and decision support. This approach is particularly relevant for TVET institutions where infrastructure constraints may limit automated ventilation control. By combining real-time monitoring with short-term prediction and guideline-based classification, the framework transforms IAQ monitoring from a reactive tool into a proactive ventilation risk management system [5],[4]. This integration provides practical support for maintenance planning, space prioritisation, and operational scheduling. These findings are consistent with recent studies highlighting the importance of predictive IAQ monitoring in dynamic indoor environments [4],[11].

From an operational perspective, the findings provide several practical implications for ventilation management in TVET institutions. Confined workshop environments should be prioritised in ventilation evaluation and improvement strategies due to their higher frequency of guideline exceedance. Predictive indoor air quality modelling can inform scheduling decisions by reducing simultaneous high-occupancy activities during peak ventilation load periods. Preventive maintenance planning may also be guided by exceedance frequency and predictive warning signals generated by the system. In addition, AIoT-based monitoring platforms can be implemented without extensive modification to existing infrastructure, making the framework feasible for institutions with limited automation capability. Collectively, the results support a structured and data-driven approach to ventilation management in training-oriented environments [16], consistent with recent AIoT-based monitoring studies [11].

Several limitations should be acknowledged. First, the study was conducted within a single TVET institution, which may limit broader generalisability. Second, the dust sensor employed measures optical particulate density and may be influenced by humidity and particle characteristics. Third, the machine learning model focused primarily on short-term prediction of CO_2 concentration; future work may extend prediction horizons or incorporate occupancy estimation. Additionally, while the model demonstrated strong performance, further validation across multiple institutions and seasonal conditions would strengthen external applicability.

Future research may extend the present work by incorporating additional indoor air quality parameters, such as formaldehyde and volatile organic compounds, to provide a more comprehensive assessment of pollutant exposure. Integrating occupancy detection mechanisms could further improve prediction accuracy by allowing the model to account explicitly for dynamic occupant behaviour. Long-term monitoring across different seasonal conditions would also provide deeper insight into variability in ventilation performance over time. In addition, deploying the proposed framework across multiple TVET institutions would enable comparative validation and strengthen its generalisability.

Future investigations may also explore integration with automated ventilation control systems to enable real-time response based on predictive outputs. These extensions would enhance both predictive precision and operational integration of the framework in educational environments [4].

5. Conclusion

This study developed and evaluated an Artificial Intelligence of Things (AIoT)-based indoor air quality monitoring and machine learning prediction framework for assessing ventilation risk in TVET institutions. Continuous monitoring of carbon dioxide concentration, dust density, temperature, and relative humidity revealed clear temporal variation driven by occupancy patterns and workshop activities. Confined workshop environments frequently exceeded recommended CO_2 thresholds, indicating recurrent ventilation inadequacy, while naturally ventilated classrooms exhibited elevated temperature and humidity levels, suggesting limited air exchange during peak occupancy. The machine learning model demonstrated reliable capability in predicting short-term indoor air quality trends and enabled early identification of potential ventilation risk before threshold exceedance. By integrating real-time monitoring, predictive analytics, and standards-based interpretation, the proposed framework supports structured ventilation assessment and preventive maintenance planning. From a practical implementation perspective, the predictive early warning capability can be deployed through simple notification mechanisms such as mobile application alerts, dashboard indicators, or audible buzzers within workshop environments. Overall, the findings demonstrate that AIoT-enabled monitoring combined with short-term prediction provides a practical and scalable approach to improving ventilation management in TVET institutions. This study successfully addressed the research objectives by demonstrating temporal variation of IAQ parameters, identifying ventilation inadequacy in selected TVET indoor spaces, developing and validating a machine learning-based prediction model, and confirming the practical applicability of AIoT-based predictive monitoring for ventilation risk assessment.

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Conflict of Interest

We declare no conflict regarding the publication of the study.

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