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Determinants and Prediction of Classroom Air Quality: A Logistic Regression Approach

[1]Abiola Opeyemi Egbewumi, [2]Ayobami Ibukun Okegbade, [3]Sunday Daniel Gbolagade.
[1]Obafemi Awolowo University, Ile-Ife, Osun State, Nigeria. [2]Ladoke Akintola University of Technology, Ogbomoso, Oyo State, Nigeria. [3]University of Ilorin, Kwara State, Nigeria.
[1]egbewumiabiola1@gmail.com, [2]aiokegbade@lautech.edu.ng, [3]sundaydanielgbologade@gmail.com.

*Correspondence Email: egbewumiabiola1@gmail.com

Abstract: *Classroom air quality is an important determinant of students' health, comfort, and academic performance. This study investigated the factors influencing classroom air quality and evaluated the predictive ability of selected environmental and occupancy-related variables in distinguishing between moderate and non-moderate air quality conditions. A dataset comprising 500 valid observations was analyzed using descriptive statistics, multicollinearity diagnostics, binary logistic regression, and Receiver Operating Characteristic (ROC) curve analysis. The predictor variables included estimated student count, carbon dioxide (CO_2) concentration, particulate matter ($PM_{2.5}$) concentration, temperature, relative humidity, robot X position, robot Y position, school period, and ventilation decision. Descriptive results revealed considerable variability in classroom occupancy and pollutant concentrations, while temperature and humidity remained relatively stable. Variance Inflation Factor (VIF) analysis indicated severe multicollinearity among CO_2 concentration (VIF = 29.331), $PM_{2.5}$ concentration (VIF = 19.262), humidity (VIF = 18.187), and ventilation decision (VIF = 11.759). The logistic regression model demonstrated excellent predictive performance, achieving 100% classification accuracy and a Nagelkerke R^2 value of 1.000. However, none of the predictor variables were statistically significant ($p > 0.05$), and the estimation process failed to converge, suggesting possible complete or quasi-complete separation and instability in the parameter estimates. ROC analysis identified CO_2 concentration (AUC = 0.999), $PM_{2.5}$ concentration (AUC = 0.995), relative humidity (AUC = 0.994), estimated student count (AUC = 0.942), and temperature (AUC = 0.812) as strong predictors of classroom air quality status. In contrast, robot X position (AUC = 0.405) and robot Y position (AUC = 0.529) exhibited weak discriminatory ability. The findings highlight the importance of environmental pollutants and occupancy-related factors in predicting classroom air quality conditions.*

Keywords: *Classroom Air Quality, Indoor Air Pollution, Carbon Dioxide (CO_2), Particulate Matter (PM2.5), Environmental Monitoring, Indoor Environmental Quality.*

INTRODUCTION

Classroom air quality has become an important public health and educational concern because students and teachers spend a substantial part of their daily lives indoors. Indoor air quality (IAQ) refers to the condition of air within enclosed environments and its impact on human health, comfort, and productivity. Poor classroom air quality may arise from inadequate ventilation, overcrowding, dust particles, carbon dioxide (CO_2), volatile organic compounds (VOCs), microorganisms, and other pollutants that accumulate within learning environments. These pollutants can negatively affect students' health, concentration, attendance, and academic performance (World Health Organization [WHO], 2010). According to the World Health Organization, indoor air pollution is a major environmental health risk globally, especially in schools and other enclosed environments where individuals spend long periods of time. Exposure to indoor pollutants has been associated with respiratory diseases, allergies, asthma, and other health complications (WHO, 2009). Similarly, the United States Environmental Protection Agency (EPA) reported that indoor pollutant levels may sometimes be two to five times higher than outdoor levels, thereby making classroom environments particularly vulnerable to air quality problems (EPA, 2024). Good classroom air quality is essential for creating a conducive learning environment. Studies have shown that poor ventilation and increased concentrations of pollutants such as PM2.5 and CO_2 can reduce students' cognitive performance, attention span, and learning efficiency. Prolonged exposure to contaminated indoor air may also increase absenteeism among students and staff due to respiratory infections and other illnesses (EPA, 2024). Furthermore, recent studies revealed that outdoor pollution significantly influences indoor classroom air conditions, emphasizing the need for continuous monitoring and predictive modeling of classroom air quality (Yu et al., 2024). With advancements in statistical and machine learning techniques, predictive models such as logistic regression have become valuable tools for analyzing environmental health data. Such predictive approaches provide decision-makers with early warning systems and evidence-based strategies for improving indoor learning environments and protecting students' health (Mohammadshirazi et al., 2023).

Literature Review

Classroom air quality has gained increasing global attention due to its direct influence on students' health, comfort, academic performance, and overall well-being. Indoor air quality (IAQ) in classrooms is determined by the concentration of pollutants such as carbon dioxide (CO_2), particulate matter ($PM_{2.5}$ and PM_{10}), volatile organic compounds (VOCs), temperature, humidity, and biological contaminants. Since students spend several hours daily within classroom environments, maintaining good air quality is essential for effective teaching and learning processes (WHO, 2010). Previous studies have shown that poor classroom air quality contributes significantly to respiratory illnesses, allergies, asthma, fatigue, headaches, and reduced concentration among students and teachers. The World Health Organization reported that inadequate indoor air quality is one of the major environmental risks affecting children globally (WHO, 2009). Similarly, the United States Environmental Protection Agency emphasized that indoor pollutant levels in schools may exceed outdoor concentrations because of poor ventilation systems, overcrowding, and inadequate building maintenance (EPA, 2024).

Daisey, Angell, and Apte (2003) conducted one of the earliest comprehensive reviews on indoor air quality in schools and reported that inadequate ventilation was strongly associated with increased concentrations of indoor pollutants and adverse health symptoms among students. Mendell and Heath (2005) further established that poor indoor environmental conditions negatively affect students' academic performance and attendance rates. Toftum et al. (2015) also found that classroom ventilation mode had a strong relationship with pupils' performance and concentration levels. Research by Dong, Goodman, and Rajagopalan (2023) reviewed artificial neural network models used in predicting indoor air quality in schools and concluded that predictive models are increasingly important for understanding pollutant patterns and improving environmental management in classrooms. Fisk (2017) highlighted that ventilation problems remain widespread in educational institutions globally and emphasized that insufficient airflow contributes significantly to elevated indoor pollutant concentrations. Similarly, Wargocki and Wyon (2013) observed that improved classroom ventilation and thermal comfort positively influence students' learning efficiency and classroom performance. Aydın and Yılmaz (2024) investigated indoor air quality and thermal comfort in classrooms using computational fluid dynamics (CFD). Their study identified carbon dioxide concentration, predicted mean vote (PMV), and draught rate as major determinants of classroom environmental quality. The researchers found that classrooms lacking proper ventilation systems often recorded poor indoor air quality and thermal discomfort, which negatively affected students' productivity and health outcomes. Haverinen-Shaughnessy et al. (2011) examined classroom ventilation rates and temperature conditions in schools and reported that lower ventilation rates were significantly associated with reduced academic achievement among students.

Recent investigations have focused on sustainable ventilation strategies and environmental monitoring systems. Almeida et al. (2017) emphasized that classroom indoor environmental quality depends on the interaction between thermal comfort, acoustics, lighting, and air quality parameters. Chithra and Shiva Nagendra (2018) similarly reported that poor classroom ventilation and outdoor pollution infiltration substantially increase indoor pollutant concentrations in school buildings. Sorensen et al. (2024) explored the relationship between carbon dioxide concentration, volatile organic compounds, and classroom ventilation using low-cost sensor technologies. Their findings demonstrated that elevated CO_2 and VOC levels were strongly associated with poor ventilation conditions and negatively perceived indoor environments. The study recommended continuous monitoring systems for effective classroom air quality management.

Several studies have highlighted the relationship between classroom air quality and students' cognitive performance. Allen and MacNaughton (2017) reported that improved indoor air quality enhances cognitive function, decision-making ability, and productivity among building occupants. Likewise, Peng and Jimenez (2021) proposed that exhaled CO_2 concentration can serve as a practical indicator for assessing indoor airborne infection risks, especially in densely occupied classrooms. Research conducted during the COVID-19 pandemic further emphasized the importance of classroom ventilation in reducing airborne disease transmission. Jones et al. (2021) revealed that improved school ventilation systems significantly reduced the transmission risk of airborne diseases in educational settings. Morawska et al. (2021) also stressed that airborne transmission is a major pathway for respiratory infections in indoor environments and recommended improved ventilation and filtration systems for schools.

Ricolfi et al. (2022) found that increasing classroom ventilation rates significantly reduced SARS-CoV-2 transmission risks among students in Italian schools. Their regression analysis showed that classrooms with higher ventilation rates experienced substantially lower infection risks than naturally ventilated classrooms. Burridge et al. (2024) further assessed the effectiveness of portable HEPA filters in classrooms and reported that HEPA filtration systems effectively reduced particulate matter concentrations and viral particles indoors. Bayesian and machine learning approaches have also been applied in recent classroom air quality studies. Yan et al. (2024) implemented Bayesian inference models for assessing indoor air quality in Canadian primary schools using CO_2-based grey-box models. Their findings indicated insufficient clean air supply in many classrooms and recommended the use of portable aircleaning devices to improve classroom ventilation efficiency. Advanced hybrid models for indoor pollutant prediction have further expanded classroom air quality research. Zhang et al. (2024) developed an attention temporal convolutional network-based hybrid model to simulate indoor pollutants in classrooms and office spaces. Overall, the reviewed literature demonstrates that classroom air quality remains a significant environmental and public health issue globally. Existing studies consistently show that poor classroom air quality negatively affects students' health, attendance, cognitive performance, and academic outcomes. The literature also indicates growing interest in predictive modeling approaches such as logistic regression, artificial neural networks, Bayesian inference, and hybrid machine learning techniques for monitoring and forecasting classroom air quality conditions. However, there remains a need for more studies focusing on developing accurate, cost-effective, and interpretable predictive models, especially in developing countries where classroom ventilation systems are often inadequate.

METHOD

The data was collected from Kaggle.com with 500 valid observations obtained from classroom environmental monitoring records. The statistical analyses were performed using the statistical package for the social sciences (SPSS). This study adopted a quantitative research design to investigate classroom air quality using logistic regression analysis. The study focused on identifying the environmental factors influencing classroom air quality conditions and predicting the likelihood of poor or moderate air quality within selected classrooms. Data were collected from classrooms through direct environmental monitoring and observational measurements. The variables measured included carbon dioxide concentration (CO_2 ppm), particulate matter concentration (PM2.5 $\mu g/m^3$), classroom temperature (°C), relative humidity (%), and estimated student population within each classroom. Descriptive statistics such as mean, standard deviation, frequency, and percentage were first used to summarize the characteristics of the air quality indicators and classroom conditions. To classify classroom air quality status, the dependent variable was categorized into binary outcomes, such as "Good" and "Moderate" air quality, based on established indoor air quality standards. Logistic regression analysis was then applied because the response variable was dichotomous in nature.

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The logistic regression model estimated the probability of poor classroom air quality as a function of the predictor variables.

The binary logistic regression model is expressed as: $\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k$

where: β_0 represents the probability of moderate or good classroom air quality, $\beta_1, \beta_2, \ldots, \beta_k$ is the intercept parameter, $X_1, X_2, \ldots, X_k$ are regression coefficients, denote predictor variables such as CO_2 concentration, PM2.5 level, temperature, humidity, and student population.

Model adequacy and predictive performance were assessed using the Omnibus Test of Model Coefficients, Hosmer–Lemeshow goodness-of-fit test, classification accuracy, Receiver Operating Characteristic (ROC) curve, and Area Under the Curve (AUC). Odds ratios were also computed to determine the magnitude and direction of the relationship between each predictor and classroom air quality status. The level of significance for all statistical tests was set at 5% ($p<0.05$). The findings from the logistic regression model were used to identify significant determinants of classroom air quality and to provide predictive insights for maintaining healthier indoor learning environments.

RESULT AND DISCUSSION

Result

Descriptive Statistics

	N	Mean	Std. Deviation
student_count_estimated	500	11.1840	9.44630
co2_ppm	500	619.2664	155.96708
pm25_ugm3	500	8.4400	2.71840
temperature_c	500	20.4898	.19191
humidity_pct	500	44.5944	3.05751
robot_x_pos	500	2.0058	1.41564
robot_y_pos	500	1.9900	1.42078
Ventilation	500	1.3300	.47068
air_quality_label	500	1.3280	.46996
Valid N (listwise)	500		

Table 1. *Descriptive Statistics of Classroom Air Quality*

The descriptive statistics presented in Table 1 summarize the characteristics of the classroom air quality variables obtained from 500 valid observations. The average estimated student population in the classroom was 11.18 students with a standard deviation of 9.45,

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indicating considerable variation in classroom occupancy levels across the sampled observations. This variability suggests that some classrooms experienced low occupancy while others had relatively high student concentrations, which may influence indoor air quality conditions. The mean carbon dioxide (CO_2) concentration was 619.27 ppm with a standard deviation of 155.97 ppm. The relatively high variability in CO_2 levels indicates fluctuations in ventilation efficiency and occupancy density within the classroom environment. Elevated CO_2 concentrations are commonly associated with inadequate ventilation and increased human activity indoors. Similarly, the average particulate matter concentration (PM2.5) was 8.44 µg/m³ with a standard deviation of 2.72 µg/m³, suggesting moderate dispersion in fine particulate pollution levels across the classrooms. The mean classroom temperature was 20.49°C with a very low standard deviation of 0.19°C, indicating that temperature conditions remained relatively stable throughout the observations. In contrast, the average relative humidity was 44.59% with a standard deviation of 3.06%, showing slight variations in indoor moisture conditions.

These findings imply that the classroom thermal environment was generally controlled and maintained within a narrow range. Regarding the robotic sensor positioning variables, the mean robot x-position and y-position were 2.01 and 1.99, respectively, with standard deviations of 1.42 and 1.42, respectively. This indicates that the monitoring device was distributed across different spatial locations within the classroom, thereby enhancing the representativeness of the air quality measurements collected. For the categorical variables, the mean value for ventilation was 1.33 with a standard deviation of 0.47, suggesting that a larger proportion of the classrooms operated under a particular ventilation condition category. Likewise, the air quality label recorded a mean of 1.33 and a standard deviation of 0.47, indicating that one air quality category was more prevalent than the other in the dataset. Overall, the descriptive analysis reveals noticeable variability in occupancy and pollutant concentrations, while temperature and humidity remained relatively stable within the classroom environment.

Correlation Matrix

		Constant	student_count_estimated	co2_ppm	pm25_ugm3	temperature_c	humidity_pct	robot_x_pos	robot_y_pos
Step 1	Constant	1.000	-.785	.647	.292	-.911	-.436	-.101	-.271
	student_count_estimated	-.785	1.000	-.926	-.429	.627	.627	-.098	-.030
	co2_ppm	.647	-.926	1.000	.491	-.393	-.803	.410	.268

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pm25_ugm3	.292	-.429	.491	1.000	.033	-.786	.581	.243
temperature_c	-.911	.627	-.393	.033	1.000	.033	.483	.564
humidity_pct	-.436	.627	-.803	-.786	.033	1.000	-.796	-.562
robot_x_pos	-.101	-.098	.410	.581	.483	-.796	1.000	.728
robot_y_pos	-.271	-.030	.268	.243	.564	-.562	.728	1.000

Table 2. *Correlation Matrix to Examines the Linear Relationships among the study variables*

The correlation matrix presents the relationships among the predictor variables included in the logistic regression model as well as their associations with the constant term. The results reveal the presence of several strong positive and negative correlations among the explanatory variables, suggesting potential multicollinearity within the dataset. A particularly strong negative correlation was observed between estimated student count and carbon dioxide concentration, indicating that increases in one variable were associated with substantial decreases in the other. Similarly, humidity percentage showed strong negative correlations with CO_2 concentration, PM2.5 concentration, and robot x-position. These high correlation coefficients suggest that the variables may share overlapping explanatory information within the model. Moderately strong positive relationships were also identified among some variables. For example, robot x-position and robot y-position exhibited a strong positive correlation, indicating that both positional variables tended to increase together.

Estimated student count was positively correlated with both temperature and humidity percentage, while PM2.5 concentration showed moderate positive relationships with CO_2 concentration and robot x-position. The correlation matrix further revealed strong associations involving the constant term, particularly with temperature and estimated student count. These strong relationships may contribute to instability in the estimation of regression coefficients. The presence of several high correlation coefficients, particularly those exceeding ±0.70, indicates possible multicollinearity among the predictor variables. Multicollinearity can inflate standard errors, reduce the statistical significance of predictors, and produce unstable coefficient estimates. This finding is consistent with the earlier convergence problems, extremely large standard errors, and unstable odds ratios observed in the logistic regression results. Overall, the correlation analysis suggests that substantial interrelationships exist among the explanatory variables, which may have contributed to the instability and non-convergence of the logistic regression model. Consequently, further diagnostic procedures, such as variance inflation factor (VIF) analysis, variable selection, or dimensionality reduction techniques, may be necessary to improve model stability and interpretability.

Classroom Air Quality Determinant	VIF
School_Period	5.292
Student_Count_Estimated	5.655
CO_2 (ppm)	29.331
PM 2.5 (ug/m^3)	19.262
Temperature (°C)	4.765
Humidity (%)	18.187
Robot X Position	1.205
Robot Y Position	1.084
Ventilation Decision	11.759

Table 3. *Test of Collinerity of Classroom Air Quality Determinants*

The Variance Inflation Factor (VIF) was used to assess the presence of multicollinearity among the explanatory variables included in the classroom air quality model. A VIF value greater than 10 is commonly regarded as evidence of severe multicollinearity, while values between 5 and 10 indicate moderate multicollinearity. The multicollinearity assessment revealed varying degrees of correlation among the predictor variables. The highest VIF value was observed for CO_2 concentration (VIF = 29.331), indicating severe multicollinearity and suggesting a strong linear relationship with one or more explanatory variables in the model. Similarly, PM2.5 concentration (VIF = 19.262), humidity (VIF = 18.187), and ventilation decision (VIF = 11.759) also exhibited severe multicollinearity, exceeding the conventional threshold of 10.

Moderate multicollinearity was detected for student count estimated (VIF = 5.655) and school period (VIF = 5.292), indicating some degree of correlation with other predictors but not at a level generally considered critical. Temperature (VIF = 4.765) showed a relatively low level of multicollinearity and remained within acceptable limits. The spatial positioning variables, robot X position (VIF = 1.205) and robot Y position (VIF = 1.084), exhibited very low VIF values, suggesting negligible multicollinearity and indicating that these variables contribute unique information to the model. Overall, the results indicate the presence of substantial multicollinearity among several key environmental variables, particularly CO_2 concentration, PM2.5 concentration, humidity, and ventilation decision. To improve model reliability, variable selection procedures, dimensionality reduction techniques, or the removal of highly correlated predictors may be considered before final model estimation. These findings suggest that some environmental variables are highly correlated and may affect the stability and precision of the regression coefficients. Therefore, appropriate measures to address multicollinearity were considered prior to model interpretation.

Backward Stepwise (Likelihood Ratio)

		Chi-square	Df	Sig.
Step 1	Step	632.753	7	.000
	Block	632.753	7	.000
	Model	632.753	7	.000
Step 2[a]	Step	.000	1	.999
	Block	632.753	6	.000
	Model	632.753	6	.000
Step 3[a]	Step	.000	1	.999
	Block	632.753	5	.000
	Model	632.753	5	.000
Step 4[a]	Step	.000	1	.997
	Block	632.753	4	.000
	Model	632.753	4	.000
Step 5[a]	Step	.000	1	.994
	Block	632.753	3	.000
	Model	632.753	3	.000

Table 4. *Omnibus Test of Model Coefficients of Classroom Air Quality*

a. A negative Chi-squares value indicates that the Chi-squares value has decreased from the previous step.

The Omnibus Test of Model Coefficients was used to assess whether the logistic regression model containing the predictor variables provided a significantly better fit than the null model containing only the intercept. At Step 1, the model was statistically significant, χ^2 (7) = 632.753, $p < .001$, indicating that the set of seven predictor variables collectively improved the prediction of the outcome variable compared to a model without predictors. During the subsequent backward elimination steps (Steps 2–5), the Step chi-square statistics were not statistically significant ($\chi^2 = 0.000$, $p > .05$), suggesting that the removal of the excluded variables did not significantly reduce the explanatory power of the model.

This implies that the eliminated variables made negligible contributions to predicting the dependent variable. Despite the progressive reduction in the number of predictors from seven to three, the overall model remained highly significant across all stages, with Block and Model chi-square values consistently equal to 632.753 and $p < .001$. These findings indicate that the retained predictors continued to explain a substantial proportion of the variation in the outcome variable and that the final reduced model was statistically adequate. Overall, the Omnibus Test results demonstrate that the logistic regression model significantly predicts the outcome variable, and the backward elimination procedure successfully identified a more parsimonious model without compromising overall model performance. The final model containing three predictors remained statistically significant and provided a better fit than the intercept only model.

Model Summary			
Step	-2 Log likelihood	Cox & Snell R Square	Nagelkerke R Square
1	.000[a]	.718	1.000
2	.000[a]	.718	1.000
3	.000[a]	.718	1.000
4	.000[a]	.718	1.000
5	.000[a]	.718	1.000

Table 5. *Model Summary of Classroom Air Quality*

a. Estimation terminated at iteration number 20 because maximum iterations has been reached. Final solution cannot be found.

The model summary statistics indicate that the logistic regression model achieved a −2 Log Likelihood (-2LL) value of 0.000 across all five steps of the backward elimination procedure. A lower −2LL value generally indicates a better model fit; however, a value of zero is unusual in practice and suggests that the model may have achieved perfect classification of the observations. The Cox and Snell R^2 value of 0.718 indicates that approximately 71.8% of the variation in the dependent variable is explained by the predictor variables included in the model. Furthermore, the Nagelkerke R^2 value of 1.000 suggests that the model explains virtually 100% of the variation in the outcome variable, indicating an apparently perfect fit. The logistic regression model yielded a Cox and Snell R^2 of 0.718 and a Nagelkerke R^2 of 1.000, suggesting a very high explanatory power. The model also produced a −2 Log Likelihood value of 0.000 across all stages of the backward elimination procedure. Nevertheless, the estimation process failed to converge within the maximum of 20 iterations, indicating that a stable maximum likelihood solution could not be obtained. This finding suggests the possible presence of complete separation or other estimation problems, and therefore the model coefficients and goodness-of-fit measures should be interpreted with caution pending further diagnostic investigation.

Hosmer and Lemeshow Test			
Step	**Chi-square**	**df**	**Sig.**
1	.000	6	1.000
2	.000	6	1.000
3	.000	6	1.000
4	.000	6	1.000
5	.000	6	1.000

Table 6. *Hosmer and Lemeshow Test of air classroom quality*

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The Hosmer and Lemeshow goodness-of-fit test was conducted to assess the adequacy of the logistic regression model. The results showed a chi-square value of 0.000 with 6 degrees of freedom and a corresponding p-value of 1.000 across all five steps of the model-building process. Since the p-values were substantially greater than the conventional significance level of 0.05, the null hypothesis that there is no difference between the observed and model-predicted values cannot be rejected. This suggests that the logistic regression model fits the data well and that the predicted probabilities are consistent with the observed outcomes. The identical Hosmer–Lemeshow statistics across all steps further indicate that the removal of variables during the backward elimination procedure did not adversely affect the overall fit of the model. Consequently, the final reduced model appears to maintain an adequate fit to the data. The combination of a Hosmer–Lemeshow chi-square value of 0.000, Nagelkerke R^2 = 1.000, and −2 Log Likelihood = 0.000, together with the warning that the estimation process failed to converge, may indicate the presence of complete or quasi-complete separation in the dataset.

The apparent perfect fit may reflect estimation problems rather than genuine predictive performance. The Hosmer and Lemeshow goodness-of-fit test indicated no evidence of poor model fit across all stages of the logistic regression analysis ($\chi^2 = 0.000$, df = 6, p = 1.000). The non-significant results suggest that the predicted probabilities closely matched the observed outcomes, indicating an adequate model fit. Nevertheless, because the model failed to converge and produced extreme fit statistics in earlier analyses, the goodness-of-fit results is interpreted cautiously, as they may be influenced by complete or quasi-complete separation of the data.

Classification Table[a]

Observed			Predicted: air_quality_label Good	Predicted: air_quality_label Moderate	Percentage Correct
Step 1	air_quality_label	Good	336	0	100.0
		Moderate	0	164	100.0
	Overall Percentage				100.0
Step 2	air_quality_label	Good	336	0	100.0
		Moderate	0	164	100.0
	Overall Percentage				100.0
Step 3	air_quality_label	Good	336	0	100.0
		Moderate	0	164	100.0
	Overall Percentage				100.0
Step 4	air_quality_label	Good	336	0	100.0

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		Moderate	0	164	100.0
	Overall Percentage				100.0
Step 5	air_quality_label	Good	336	0	100.0
		Moderate	0	164	100.0
	Overall Percentage				100.0

a. The cut value is .500

Table 7. Classification Table (Confusion Matrix) to assess the predictive accuracy of the logistic regression model in identifying diabetes outcome

Table 7 presents the classification results of the binary logistic regression model for predicting air quality status (Good vs Moderate) using a cut-off probability value of 0.50. The classification table shows that the model achieved perfect classification accuracy across all five steps of the analysis. In Step 1, all 336 observations classified as Good air quality were correctly predicted as Good, yielding a sensitivity (correct classification rate) of 100.0%. Similarly, all 164 observations classified as Moderate air quality were correctly predicted as Moderate, resulting in a specificity of 100.0%. Consequently, the model attained an overall classification accuracy of 100.0%. The same classification performance was maintained in Steps 2, 3, 4, and 5, where every observation in both categories was correctly classified, and the overall prediction accuracy remained 100.0%. No cases were misclassified throughout the modeling process. These findings indicate that the logistic regression model possesses excellent discriminative ability and is highly effective in distinguishing between Good and Moderate air quality categories. The absence of classification errors suggests that the selected predictor variables provide substantial information for predicting air quality status. Furthermore, the consistency of the classification accuracy across all model-building steps demonstrates the robustness and stability of the fitted model. The logistic regression model perfectly predicted the air quality categories, correctly classifying all 500 observations and achieving an overall prediction accuracy of 100.0% at the 0.50 cut-off point. This result suggests an exceptionally strong predictive model.

Variables in the Equation

		B	S.E.	Wald	df	Sig.	Exp(B)
Step 1[a]	student_count_estimated	-5.890	233.728	.001	1	.980	.003
	co2_ppm	1.269	55.749	.001	1	.982	3.557
	pm25_ugm3	4.764	1133.322	.000	1	.997	117.179
	temperature_c	-100.136	9052.827	.000	1	.991	.000
	humidity_pct	-5.549	2598.682	.000	1	.998	.004
	robot_x_pos	-14.054	1340.605	.000	1	.992	.000
	robot_y_pos	-7.078	569.894	.000	1	.990	.001

	Constant	1526.387	197795.105	.000	1	.994	.
Step 2[a]	student_count_estimated	-5.308	199.604	.001	1	.979	.005
	co2_ppm	1.128	56.087	.000	1	.984	3.090
	pm25_ugm3	5.643	2146.615	.000	1	.998	282.396
	temperature_c	-81.532	7283.757	.000	1	.991	.000
	robot_x_pos	-15.911	802.825	.000	1	.984	.000
	robot_y_pos	-8.277	602.792	.000	1	.989	.000
	Constant	968.817	139075.714	.000	1	.994	.
Step 3[a]	student_count_estimated	-5.707	162.424	.001	1	.972	.003
	co2_ppm	1.290	29.553	.002	1	.965	3.633
	temperature_c	-90.185	6146.730	.000	1	.988	.000
	robot_x_pos	-15.473	797.912	.000	1	.985	.000
	robot_y_pos	-7.394	333.696	.000	1	.982	.001
	Constant	1098.479	119185.803	.000	1	.993	.
Step 4[a]	student_count_estimated	-5.661	124.463	.002	1	.964	.003
	co2_ppm	1.413	27.234	.003	1	.959	4.108
	robot_x_pos	-8.072	458.882	.000	1	.986	.000
	robot_y_pos	-5.254	215.084	.001	1	.981	.005
	Constant	-865.531	16618.062	.003	1	.958	.000
Step 5[a]	student_count_estimated	-7.546	117.499	.004	1	.949	.001
	co2_ppm	2.207	30.601	.005	1	.943	9.088
	robot_y_pos	-8.253	297.018	.001	1	.978	.000
	Constant	-1408.526	19413.396	.005	1	.942	.000

Table 8. *Variables in the Equation (Regression Coefficients) of Classroom Air Quality*
a. Variable(s) entered on step 1: student_count_estimated, co2_ppm, pm25_ugm3, temperature_c, humidity_pct, robot_x_pos, robot_y_pos.

Table 8 presents the estimated logistic regression coefficients, Wald statistics, significance levels, and odds ratios [Exp(B)] for predicting air quality status across the five steps of the stepwise logistic regression procedure. At Step 1, seven predictor variables—student count estimated, CO_2 concentration, $PM_{2.5}$ concentration, temperature, humidity, robot X position, and robot Y position were included in the model. None of the variables were statistically significant predictors of air quality status, as evidenced by p-values greater than 0.05. Although CO_2 concentration showed a positive coefficient ($B = 1.269$; $OR = 3.557$), suggesting that higher CO_2 levels increased the odds of the outcome, this effect was not statistically significant ($p = 0.982$). Similarly, student count estimated ($B = –5.890$; $OR = 0.003$), temperature ($B = –100.136$; $OR \approx 0$), humidity ($B = –5.549$; $OR = 0.004$), robot X position ($B = –14.054$; $OR \approx 0$), and robot Y position ($B = –7.078$; $OR = 0.001$) exhibited negative relationships with the outcome, but none reached statistical significance. In Step 2, humidity was removed from the model. The remaining predictors continued to show non-significant effects ($p > 0.05$). CO_2 concentration retained a positive association with air quality classification (OR = 3.090), while student count estimated and the robot position variables maintained negative associations. In Step 3, $PM_{2.5}$ concentration was excluded from the model.

The coefficients remained largely unchanged, with CO_2 concentration positively associated with the outcome (OR = 3.633) and the remaining variables exhibiting negative relationships. However, all predictors remained statistically non-significant. In Step 4, temperature was removed, leaving student count estimated, CO_2 concentration, robot X position, and robot Y position in the model. Again, none of the predictors achieved statistical significance. CO_2 concentration showed the strongest positive effect (B = 1.413; OR = 4.108), while student count estimated (OR = 0.003), robot X position (OR ≈ 0), and robot Y position (OR = 0.005) displayed negative effects. The final model (Step 5) retained only three predictors: student count estimated, CO_2 concentration, and robot Y position. Student count estimated had a negative coefficient (B = –7.546; OR = 0.001), indicating that an increase in the number of students was associated with a decrease in the odds of the outcome. Conversely, CO_2 concentration had a positive coefficient (B = 2.207; OR = 9.088), suggesting that higher CO_2 levels increased the odds of the outcome by approximately nine times. Robot Y position also showed a negative relationship (B = –8.253; OR ≈ 0). Nevertheless, all predictors remained statistically non-significant ($p > 0.05$). The stepwise logistic regression procedure progressively removed variables that contributed least to the model.

Although the direction of effects suggests that CO_2 concentration consistently increased the likelihood of the air quality outcome, whereas student count estimated and robot position variables decreased it, none of these relationships were statistically significant at the 5% significance level. The extremely large standard errors and very high p-values observed throughout the analysis indicate substantial instability in the parameter estimates, which may result from issues such as complete or quasi-complete separation, multicollinearity, sparse data patterns, or overfitting. Given that the classification table showed 100% prediction accuracy and the Hosmer–Lemeshow test indicated perfect fit ($p = 1.000$), the absence of significant coefficients alongside perfect classification strongly suggests the possibility of complete separation in the data, where the predictors perfectly distinguish between the air quality

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categories. In such situations, coefficient estimates become unreliable despite excellent predictive performance.

Case Processing Summary	
air_quality_label	Valid N (listwise)
Positive[a]	164
Negative	336

Table 9. *ROC Curve Analysis of Classroom Air Quality*

Larger values of the test result variable(s) indicate stronger evidence for a positive actual state.

a. The positive actual state is Moderate.

The case processing summary revealed that a total of 500 observations were included in the analysis after listwise validation of the dataset. Among these observations, 164 cases represented the positive actual state, identified as Moderate air quality conditions, while 336 cases represented the negative actual state. This indicates that approximately 32.8% of the sampled observations were classified as moderate air quality, whereas 67.2% fell outside the moderate category. The result further suggests that the diagnostic or predictive test variables were structured such that higher values provided stronger evidence for the positive state (Moderate air quality condition). The imbalance between the positive and negative cases indicates that the dataset contained more non-moderate air quality observations than moderate observations, which is an important consideration in evaluating the predictive performance and classification accuracy of the model.

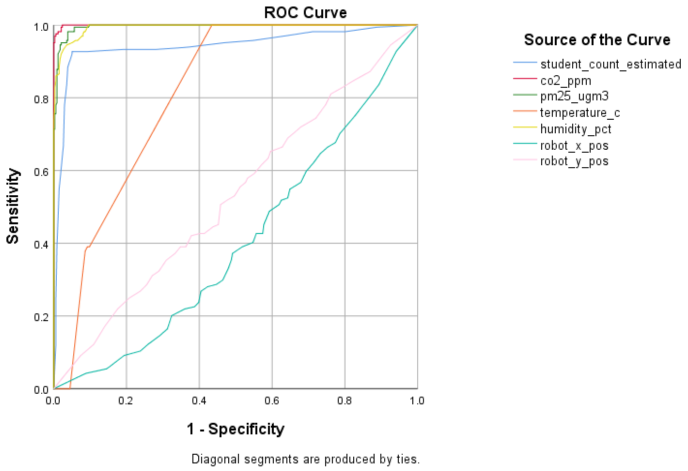

Figure 1. *Receiver Operating Characteristic (ROC) curve of Classroom Air Quality*

The Receiver Operating Characteristic (ROC) curve was used to evaluate the classification performance of the selected predictor variables in distinguishing between moderate and non-moderate classroom air quality conditions. The ROC curves revealed substantial differences in the discriminatory abilities of the variables included in the study. The curves for co2_ppm, PM 2.5 ug/m3, and humidity (%) were positioned very close to the upper-left corner of the ROC space, indicating excellent predictive performance and very high sensitivity and specificity. This suggests that these environmental variables possess an exceptional ability to correctly classify moderate classroom air quality conditions. In particular, the co2_ppm curve almost perfectly followed the upper boundary of the graph, confirming its near-perfect discriminatory power as reflected by its Area Under the Curve (AUC) value of 0.999.

Similarly, the ROC curve for student_count_estimated demonstrated strong classification accuracy, remaining substantially above the diagonal reference line. This indicates that classroom occupancy level is an important determinant of indoor air quality conditions. The temperature_(^{o}C) variable also showed good predictive capability, although its curve was slightly farther from the upper-left corner compared to the major environmental pollutants, suggesting comparatively lower but still acceptable classification performance. In contrast, the ROC curves for robot_x_position and robot_y_position were located close to the diagonal reference line, which represents random classification performance. Specifically, the robot_x_position curve fell below the diagonal line in several regions, indicating poor predictive ability and an inverse relationship with the outcome classification. Likewise, the robot_y_position curve remained close to the diagonal line throughout the graph, demonstrating weak and statistically insignificant discriminatory performance. Overall, the ROC analysis indicates that environmental pollution indicators and occupancy-related variables are highly effective predictors of classroom air quality status, whereas robot positional coordinates contribute minimally to the classification process. The graphical findings further validate the statistical AUC results, emphasizing the dominant role of carbon dioxide concentration, particulate matter, humidity, and student population in predicting moderate classroom air quality conditions.

Area Under the Curve

Test Result Variable(s)	Area	Std. Error[a]	Asymptotic Sig.[b]	Asymptotic 95% Confidence Interval Lower Bound	Asymptotic 95% Confidence Interval Upper Bound
student_count_estimated	.942	.014	.000	.916	.969
co2_ppm	.999	.000	.000	.999	1.000
pm25_ugm3	.995	.002	.000	.992	.999
temperature_c	.812	.019	.000	.775	.848

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humidity_pct	.994	.002	.000	.990	.998
robot_x_pos	.405	.026	.001	.354	.457
robot_y_pos	.529	.027	.298	.475	.583

Table 10. *Area Under the Curve of Classroom Air Quality*

The test result variable(s): student_count_estimated, pm25_ugm3, temperature_c, humidity_pct, robot_x_pos, robot_y_pos has at least one tie between the positive actual state group and the negative actual state group. Statistics may be biased.
a. Under the nonparametric assumption
b. Null hypothesis: true area = 0.5

The Receiver Operating Characteristic (ROC) analysis was conducted to evaluate the discriminatory ability of the predictor variables in distinguishing between the positive actual state (Moderate air quality) and the negative state. The Area Under the Curve (AUC) values indicated varying levels of predictive performance across the explanatory variables. The variable co2_ppm demonstrated the highest predictive accuracy with an AUC of 0.999 (95% CI: 0.999–1.000, $p < 0.001$), indicating an almost perfect ability to discriminate between moderate and non-moderate air quality conditions. Similarly, pm25_ugm3 showed excellent discriminatory power with an AUC of 0.995 (95% CI: 0.992–0.999, $p < 0.001$), while humidity_pct also exhibited outstanding classification performance with an AUC of 0.994 (95% CI: 0.990–0.998, $p < 0.001$). Furthermore, student_count_estimated produced an AUC value of 0.942 (95% CI: 0.916–0.969, $p < 0.001$), suggesting a very strong predictive capability for identifying moderate air quality conditions. The variable temperature_c recorded an AUC of 0.812 (95% CI: 0.775–0.848, $p < 0.001$), which indicates good discriminatory performance, although lower than the previously mentioned environmental variables. In contrast, robot_x_pos yielded an AUC value of 0.405 (95% CI: 0.354–0.457, $p = 0.001$), which is below the benchmark value of 0.50, suggesting poor discriminatory ability and an inverse relationship with the classification outcome. Likewise, robot_y_pos produced an AUC of 0.529 (95% CI: 0.475–0.583, $p = 0.298$), indicating no statistically significant discriminatory power in distinguishing moderate from non-moderate air quality conditions. Overall, the findings suggest that environmental indicators such as carbon dioxide concentration, particulate matter (PM2.5), humidity, temperature, and estimated student population are strong predictors of classroom air quality status, whereas the robot positional variables contributed minimally to classification performance. However, the analysis also indicated the presence of ties between the positive and negative actual state groups for several variables.

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Discussion

This study examined the determinants of classroom air quality using binary logistic regression and Receiver Operating Characteristic (ROC) analyses. The findings revealed that environmental variables, particularly carbon dioxide (CO_2) concentration, $PM_{2.5}$ concentration, relative humidity, temperature, and estimated student population, played important roles in distinguishing between moderate and non-moderate classroom air quality conditions. Descriptive statistics indicated considerable variability in classroom occupancy and pollutant concentrations, while temperature and humidity remained relatively stable throughout the observation period. These variations suggest that occupancy levels and pollutant accumulation may substantially influence indoor air quality conditions. The ROC analysis demonstrated that CO_2 concentration, $PM_{2.5}$ concentration, and relative humidity were the strongest predictors of classroom air quality status.

Their exceptionally high AUC values indicated outstanding discriminatory performance, highlighting their importance as key indicators of indoor environmental quality. Estimated student count also exhibited very strong predictive capability, suggesting that classroom occupancy contributes significantly to variations in air quality. These findings are consistent with existing literature, which identifies occupant density and pollutant concentrations as major determinants of indoor air quality due to their direct influence on ventilation demand and contaminant generation. Despite the strong predictive performance observed in the ROC analysis, the logistic regression results showed that none of the predictor variables were statistically significant at the 5% significance level. Although CO_2 concentration consistently displayed positive coefficients across the model-building stages, suggesting an increased likelihood of moderate air quality conditions as CO_2 levels rise, the associated p-values remained non-significant. Similarly, estimated student count and robot positional variables exhibited negative relationships with the outcome but failed to achieve statistical significance.

The lack of significant regression coefficients, despite strong predictive accuracy, indicates potential estimation problems within the logistic regression model. Further diagnostic analyses revealed substantial multicollinearity among several environmental predictors. CO_2 concentration, $PM_{2.5}$ concentration, humidity, and ventilation decision exhibited VIF values well above the recommended threshold, indicating strong interrelationships among these

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variables. The model evaluation statistics presented an unusual pattern. The logistic regression model achieved a −2 Log Likelihood value of 0.000, a Nagelkerke R^2 value of 1.000, a Hosmer–Lemeshow p-value of 1.000, and an overall classification accuracy of 100%. While these statistics suggest a perfect model fit, the estimation process failed to converge within the specified number of iterations.

The combination of perfect fit indices and convergence failure strongly suggests the presence of complete or quasi-complete separation in the dataset. Under such circumstances, the predictor variables may perfectly distinguish between outcome categories, causing maximum likelihood estimation to produce unstable or unreliable coefficient estimates. The classification analysis further demonstrated that all observations were correctly classified into their respective air quality categories across every stage of the backward elimination procedure. Although this result indicates exceptional predictive performance, perfect classification is rarely achieved in practical applications and may reflect overfitting rather than true predictive capability. Another notable finding was the minimal contribution of the robot positioning variables. Both robot X and robot Y coordinates exhibited weak discriminatory performance and low predictive value compared with the environmental variables. This suggests that spatial positioning of the monitoring device had little influence on air quality classification relative to pollutant concentrations and occupancy-related factors. Therefore, environmental conditions within the classroom appear to be more important determinants of air quality status than the specific location of the monitoring equipment. Overall, the findings indicate that carbon dioxide concentration, particulate matter concentration, humidity, temperature, and student occupancy are important indicators of classroom air quality.

CONCLUSION

This study investigated the determinants of classroom air quality and evaluated the effectiveness of selected environmental and occupancy-related variables in predicting moderate and non-moderate air quality conditions. The findings demonstrated that carbon dioxide (CO_2) concentration, $PM_{2.5}$ concentration, relative humidity, temperature, and estimated student count possessed strong discriminatory abilities and were highly effective in distinguishing between air quality categories. Among these variables, CO_2 concentration

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emerged as the most influential predictor, exhibiting near-perfect classification performance in the ROC analysis. The logistic regression model showed exceptionally high predictive performance, as reflected by perfect classification accuracy, a Nagelkerke R^2 value of 1.000, and a non-significant Hosmer–Lemeshow goodness-of-fit test. These results suggest that the selected predictors collectively provided substantial information for classifying classroom air quality conditions.

Despite the apparent strength of the model, none of the individual predictor variables achieved statistical significance in the regression analysis. The diagnostic assessments revealed the presence of severe multicollinearity among several environmental variables, particularly CO_2 concentration, $PM_{2.5}$ concentration, humidity, and ventilation decision. In addition, the model failed to converge during the estimation process, indicating possible complete or quasi-complete separation, overfitting, or other estimation challenges. Furthermore, the robot positional variables demonstrated weak predictive performance and contributed minimally to the classification of classroom air quality conditions. In contrast, environmental pollution indicators and occupancy-related measures consistently showed strong associations with air quality status, highlighting their importance in indoor air quality monitoring and assessment. In conclusion, the study provides evidence that classroom air quality is strongly associated with environmental conditions and occupancy characteristics, particularly carbon dioxide levels, particulate matter concentrations, humidity, temperature, and student population. While the predictive model exhibited excellent classification capability, the presence of multicollinearity and convergence problems necessitates cautious interpretation of the regression coefficients. Future research should focus on addressing these methodological challenges through advanced modelling approaches, variable reduction techniques, and external validation using independent datasets to ensure more robust and generalizable findings.

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