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RESEARCH ARTICLE

# Investigating Indoor Air Quality (IAQ) and Sick Building Syndrome Symptoms (SBSS) using generalized linear model

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**Abstract:**

Prediction of Indoor Air Quality and Sick Buildings Syndrome Symptoms (SBSS) was developed to predict the relative humidity (RH) inside the building. The developed generalized linear model (GLM) model consider relative humidity as dependent variables and independent variables consists of Indoor Air Quality Parameters (IAQ) such as ventilation performance indicator, physical and chemical parameters besides present SBSS. Primary data was collected, and distribution of questionnaires was conducted at the same time. Three models were developed which named Model A, Model B and Model C. A logarithmic link function was considered with a Poison probability distribution. Particular attention was dedicated to cases with Relative Humidity<mean (Model A), Relative Humidity mean range (Model B) and Relative Humidity >mean (Model C). Results indicate that best performance was Model A which outperformed Model B and Model C. It showed that there were a few contributions of SBS and IAQ towards RH inside the building such as dizziness, drowsiness, heavy headed, headache, temperature and $PM_{10}$. This study showed that Model A ($R^2$=96.8%) outstand Model B (86.9%) and Model C (93.5%) due to the data collected mostly distribute lower than mean value of RH.

**Keywords:** Indoor Air Quality, Prediction, SBSS, School, Generalized Linear Model

## 1. INTRODUCTION

Develop and developing countries people spent almost 90% per day their times indoors which become most important and gain growing attention due to larger proportion of their time in indoor area either in offices or homes (Cheng et al., 2022; Pottier et al., 2021). Previous research studies showed that indoors air is more contaminated than ambient air (Mansor et al.,2020; Awada et al., 2022). The most common indoor air pollutants that been monitored was formaldehyde (HCHO), particulate matter (PM) or known as respirable particulates, volatile organic compound (VOCs), carbon monoxide (CO), carbon dioxide ($CO_2$) and ozone ($O_3$) (Mentese et al., 2020; Wolkoff., 2018; Ye et al., 2014). Assessments of indoor air quality are carried out for various reasons, which include identifying sources of pollutants in indoor environments and assessing their potential adverse effects on the health of occupants. Another purpose is to determine whether indoor air quality meets recommended standards and guidelines for health and comfort, as well as to evaluate the effectiveness of ventilation systems and other measures for controlling indoor air quality. Such assessments also aim to identify potential risks associated with indoor air pollution and develop strategies for minimizing them. Ultimately, indoor air quality assessments provide valuable information and guidance to building occupants and owners on maintaining a healthy and comfortable indoor environment. Sick Building syndrome (SBS) is one of the scopes to determine the IAQ which covers unspecified adverse health effects due to poor IAQ. The wording “syndrome” used in this scope due to unidentified factors or sources have not been fully confirmed yet (Yin et al., 2022; Lucialli et al., 2020). Previous research has demonstrated that prolonged exposure to poor indoor air quality can lead to various health problems and symptoms, which vary in severity depending on the intensity of the indoor air pollution sources (Aziz et al., 2023). Buildings that have been found to cause such problems are referred to as "sick buildings". Sick building syndrome (SBS) is characterized by a wide range of personal symptoms that are believed to be caused by exposure to indoor environmental sources, although the exact cause of these symptoms remains unclear. A combination of multiple factors or single factors was the cause of SBS. Roughly, the factors can be caused by humidity, insufficient ventilation, chemical pollutants which caused by indoor environments, light, biological pollutants which can comes from external sources and temperature (Kwon et al., 2019; Argunhan et al., 2018). WHO identified SBS by complaints that used as one indicator to identify the occupants' symptoms such as general health problems or neurotoxic, nose, eyes and throat irritation, skin irritation, odours and taste sensations and nonspecific hypersensitivity. Latest studies showed that potential sources that contribute to SBS was paints, cleaning agents, building products, combustions of fuels, cosmetics and many more (Abdullah et al., 2018) air pollution and prediction modelling can be used to inform in advance contingency plans which helps in reducing the adverse impacts of air pollution on population, especially on the sensitive group, as their internal organs are fragile. The complexity of indoor air pollutants and SBS can be represented by Generalized Linear Models (GLM) because of its data contain qualitative and quantitative data and GLM can be used in different types of data which mainly in prediction and therefore giving early useful information for community. This study was conducted to develop the relationship between IAQ with SBS using GLM which important for occupants' safety and comfortability. Good Indoor Air Quality (IAQ) contributes to a favourable environment for occupants, the performance of teachers and staff and a sense of comfort, health, and well-being. These elements combined to assist a building in its core mission, which is educating community (Ziang et al., 2022; Rosbach et al., 2016). Studies of air pollutants movement indicate that indoor levels of pollutants may be two to five times and occasionally more than 100 times higher than outdoor levels. Performance ventilation indicator, chemical and physical parameter was important to be measured to investigate how outdoor sources influence air flow inside the buildings. Data collected was utilized for determine the acceptance of the pollutants inside the building with the standard which is Industrial Code of Practice Indoor Air Quality (ICOP-IAQ) 2010 was important as a baseline data. Due to the complexity of indoor air pollutants, qualitative and quantitative model used which is better compared to others basic model because no assumptions are being made throughout the modelling process, which can be used in different scenarios which therefore give more accurate and precise indoor air quality of real-world conditions (Zhai et al., 2020; Korsavi et al., 2022; Derby et al., 2016). Model prediction is important for regulatory agencies in setting indoor air quality regulations to protect our young children health and well-being.

## 2. MATERIALS AND METHODS

### 2.1 Study Area and Data Collection

Sekolah Kebangsaan Tanjung Gelam (103° 4'50.64"E, 5°24'46.89"N) was choose as study area. The school located at Kuala Nerus district at Terengganu, Malaysia. The study was conducted in the teacher's room at level 3 of the school buildings. The teacher's room consists of 11 teachers. Age range of the teachers involved were <25 years old (54.5%), 25-39 years old (9.1%), 40-55 years old (27.3%) and >55 years old (9.1%). Site selection was chosen to determine the comfortability of the teachers in their rooms. This is due to the study area used ceiling fans rather than air conditioning. Besides ceiling fans, the rooms ventilation was windows and doors. Layout and location of the classrooms showed in Figure 1.

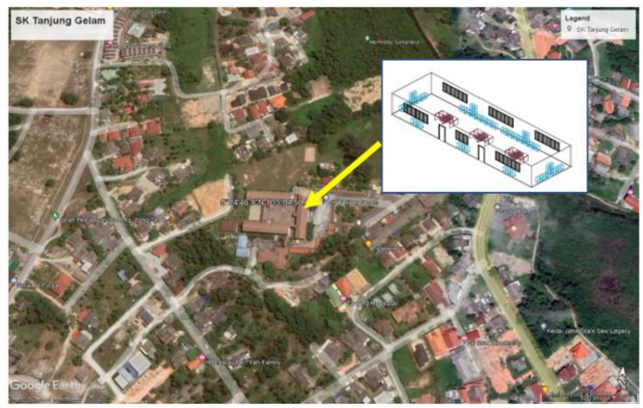



Figure 1. Study area

This study was measured physical, chemical and ventilation performance indicators of the study are. Chemical parameters consist of carbon monoxide (CO) ppm, formaldehyde (HCHO) ppm, respirable particulate (PM) μg/m$^3$, and total volatile organic compound (TVOC) ppm. The physical parameters included relative humidity (RH) %, temperature (T) ºC, and air movement (AM) m/s and the ventilation performances indicators were carbon dioxide ($CO_2$) ppm. Primary data monitored consists of 10 days of working hours for sampling with 10 minutes time intervals and distribution of questionnaires was conducted at the same time. Table 1 showed the instruments used to measure ventilation performances indicators, chemical and physical parameters. Based on Industrial Code of Practice (ICOP) 2010, instruments placed at a height between 75 and 120 cm from the floor. Questionnaire distribution involved teachers inside the buildings that have been monitored. The questionnaire consists of 5 section that involved general information, background factors, nature of occupation, environmental conditions and symptoms that involved past and present symptoms which adopt from Industrial Code of Practice Indoor Air Quality (ICOP-IAQ 2010). Present symptoms consist of drowsiness, feeling heavy headed, headache, dizziness, nausea/vomiting, cough, irritated and stuffy nose and more, while for past situation consists of the situation at the study area for the past three months such as the temperature eithers it is too low or high, draught, dry air, unpleasant odours, dust and dirt and passive smoking.

Table 1. List of instruments

| Instruments | Parameters |
|---|---|
| TSI Climomaster Model 9545 | Temperature, relative humidity, and air movement |
| DustTrak DRX Aerosol Monitor 8533 | RSP ($PM_{10}$, $PM_{2.5}$) |
| Q-Trak Indoor Air Quality Monitor 7575 | Carbon dioxide and carbon monoxide |
| Formaldehyde meter<br>Portable VOC Monitor MiniRae 30000 | Formaldehyde<br>TVOC |

## 2.2 Data Analysis

Descriptive analysis was conducted due to its fundamental component in helping to analyze the data. There are several descriptive statistics that were evaluated in this study such as mean, median, mode, standard deviation, variance, and range. Statistical distribution measures, also known as descriptive statistics or summary statistics are used to summarize the information from collected or set of data. In this study mean values was used to compare with the ICOP-IAQ 2010 guidelines

Correlation analysis was also used in this study which used to determine the relationship between two variables 'x' and 'y'. In correlation, there is no difference between dependent and independent variables. Correlation can be positive or negative. When the two variables move in the same direction, for instance, one variable increases, followed by another variable, then the variables are positively correlated (r=1). However, when two variables are inversely proportional to one another, then the variable is negatively correlated (r=- 1).

In addition, Generalized Linear Model (GLM) commonly used to estimate associations between the total carbon footprint and the sources of the emission was also used in this study (Mentese et al., 2020). Therefore, GLM was applied to find associations between source of $CO_2$ and total carbon footprint data of this study. The GLM are junction of linear and non-linear models with a distribution of exponential family (normal, inverse normal, binomial, Poisson and gamma functions) and logistic models. The GLM is formed by the following three components (Tong et al., 2018):

- Random components: n values of the response variable ($y_i$, ……$y_n$)
- Systematic component: a linear structure for the regression model ( $\boldsymbol{\eta = \beta x^T}$ ), where $\boldsymbol{x^T} = (\boldsymbol{1, x_{i1}, x_{i2}, \dots, x_{in}})^{\boldsymbol{T}}$ , $i$=1…m represents the explanatory or independent variables and;
- Link function: a montone and differentiable function $g$, which connects the random and systematic components relating dependent variable mean (μ) with the linear structure in equation 1:

$$\boldsymbol{g(\mu_I) = x_i^t \beta, i = 1 \ldots\ldots K} \quad (1)$$

where (β = β1 β2 … βp) are the values of parameters to be estimated. Thus, if we consider for the function g the identity function we have:

$$\boldsymbol{g(\mu_i) = \mu_i} \quad (2)$$

Then

$$\boldsymbol{\mu_i = E(Y_i) = x_i^t \beta} \quad (3)$$

The resulting model is the linear regression model. If alternatively, consider the function g as a logarithmic function and $Y_i$ has a Gamma distribution, then the model will result in a Gamma regression model and each term $\beta_i$ is the effect of variable $X_i$ in $g(\mu_i)$ (Mentesene et al., 2020; Pekey et al., 2008; Lu et al., 2015; Ul-Saufie et al., 2013). Each $\beta_i$ represents the "effect" of variable $X_i$ in the function $g(\mu_i)$. In this case the objective is to estimate indoor air quality based on other variables, like past and present symptoms besides indoor air quality parameters that consists of physical and chemical parameter (Mentese et al., 2020; Lazovic et al., 2015). Statistical Package software for Social Sciences SPSS 10.0 for windows was used to build and analyse the model.

Each distribution has unique link function. The distribution most used on the estimation of air pollution health impacts in Gamma function (Aroonsrimorakat et al., 2013; Soleimani et al., 2019), of which link function is $\boldsymbol{\eta} = \mathbf{log}(\mu)$,then $\mu = \boldsymbol{e^i}$. Thus, η follows a linear model's assumptions rather than μ, using matrix notation showed in Table 1:

$$\mathbf{log}(\mu) = \boldsymbol{\beta x^T + f} \quad (4)$$

Table 2. General parameter

| **Model Information** | |
|---|---|
| Dependent Variable | RH |
| Probability Distribution | Gamma |
| Link Function | Log |

## 3. RESULTS AND DISCUSSION

Study area consists of 11 workers which are teachers that classified into 68.4% was female and 31.6% male. 52.63% of the occupants was working at the stay area more than 5 years. Respondents consists of several age stage which are 40-57 years old (57.9%), 25-29 years old (15.8%), <25 years old (21.1%) and >55 years old (5.3%). Most of the occupant believe that present symptoms inside the building was cause due to environment of workstation was 84.2%, 10.5% not agreed that environment of the workstation was cause the symptoms and 5.3% was not sure the cause of the present symptoms. These findings were important to determine the background of the study area. Table 3 showed descriptive statistics for indoor air quality (IAQ) in the study area and most of the time comply with the ICOP-IAQ 2010. All chemical parameters were under limit, but physical parameters have a few times that follows the standard but for physical parameters there were a few times that the air movements were insufficient due to the value was lower than the standards range and the temperature was exceed the limit for a few times which cause decrease comfortability among the occupants inside the teacher's room.

Table 3. Mean of the study area and Standard value of ICOP-IAQ

| Parameter | Mean | Standard ICOP-IAQ |
|---|---|---|
| T ($^{O}$C) | 27-31.45 | 23-26 |
| RH (%) | 70.45-83.35 | 40-70 |
| AM (m/s) | 0.105-0.18 | 0.15-0.50 |
| $CO_2$ (ppm) | 353-432.5 | <1000 |
| CO (ppm) | 0-0.8 | 10 |
| HCHO (ppm) | 0.02-0.04 | 0.1 |
| $PM_{10}$ (mg/m$^3$) | 0.0255-0.0385 | 0.15 |
| $PM_{2.5}$ (mg/m$^3$) | 0.0235-0.034 | 0.15 |
| $PM_1$ (mg/m$^3$) | 0.0215-0.0335 | 0.15 |

GLM models were used to investigate the complex relationships between the physical, chemical, ventilation performance indicators and sick building syndrome symptoms in the teacher's room.

$$In\ [RH] = \alpha + \beta_1\, var_1 + \beta_2\, var_2 + ..\beta_n\, var_n) \qquad (5)$$

Based on these results, RH can be expressed as the product of exponential terms:

$$[RH] = e^{(\alpha+\beta_1\, var_1+\beta_2 var_2+..\beta_n\, var_n)} \qquad (6)$$

The first term contains the regression intercept, and the rest terms contain binary variables, originated from GLM model as explained above. This methodology as applied to three tested models A, B and C. The three models presented in table 4 differ only in data considered. In model A, we considered the low temperature of observations recorded. In model A we considered the observations recorded standard (RH<70.45%), Model B was (RH70.45-83.35) and Model C (RH>83.33%). These considerations are shortly resumed in table 3.

Table 4. Specific models short description.

| Model | Restriction | Dependant variable | covariates |
|---|---|---|---|
| A | RH< 70.45 | Temp min | Headache, Feeling heavy headed, Dizziness, Skin rash itchiness, T, $PM_{10}$ |
| B | RH 70.45-83.35 | Temp med | Headache, Skin rash, Temperature and $PM_{10}$ |
| C | RH >83.335 | Temp max | Headache, T max, Feeling heavy headed, $CO_2$, $PM_{2.5}$, Hoarse dry throat |

The $\beta$ coefficient obtained with methodology implemented for two models.

| Model | Equation |
|---|---|
| A | $In\ RHmin = 1.392 + 0.265[Headache, 1] + 0.219[Headache, 2] - 0.240[Feeling\ Heavy\ Headed, 1] - 0.201[Feeling\ Heavy\ Headed, 2] - 0.080[Dizziness, 1] - 0.024[Skin\ itchiness, 1] - 0.031[Skin\ Itchiness, 2] + 0.091\ Tmin + 0.0337PM_{10}$ |
| B | $In\ RH\ med = 6.441 + 0.067[Headache, 1] + 0.036[Headache, 2] - 0.019[Dizzines, 1] + 0.001[Skin\ rash, 1] + 0.005[Skin\ rash, 2] - 0.070\ T - 1.524PM_{10}$ |

C

$$\begin{aligned} InRH\ max &= 4.555 + 0.030\{Headache, 1] + 0.027[Headache, 2] + 0.006T \\ &- 0.027[Feeling\ Heavy\ Headed, 1] \\ &- 0.024[Feeling\ Heavy\ Headed, 2] \\ &- 0.001CO_2 + 0.136PM_{2.5} \\ &- 0.004[Hoarse\ and\ Dry\ Throat, 1] \\ &- 0.007\ [Hoarse\ and\ Dry\ Throat] \end{aligned}$$

Equation above showed that RH was increased by 0.265 and 0.218 unit when respondent was feeling [headache, 1] variables [yes, often] or [headache, 2] for [yes, sometimes], and go up by one unit, 0.240 or 0.201 unit in decreasing one unit of [Feeling heavy headed,1] or [Feeling heavy headed, 2], 0.080 unit for the decrease in one unit of [Dizzines,1], 0.031 unit when [skin itchiness,2] decreased by one unit, 0.091 unit increase in one unit of temperature (T) and 0.337 unit in increasing one unit of $PM_{10}$ for Model A. Basically RH has interaction with increasing of headache, temperature and $PM_{10}$ and inversely proportional with skin itchiness, feeling heavy headed and dizziness (Abdullah et al., 2019). Previous study stated that there is increasing evidence that air pollution, and particularly small particulate pollutants, can induce transient increases in the risk—or triggering—of myocardial infarction, stroke, congestive heart failure, ventricular arrhythmias, asthma, and respiratory infections. A few small studies have suggested that various forms of air pollution may be linked to headache, as have two Canadian studies that compared trends in hospital visits for headaches and pollutant levels. To our knowledge, no studies have evaluated whether indoor air pollution and particularly fine particulate matter which triggers migraines or other headache syndromes using case-crossover physical parameter such as temperature and relative humidity, which directly compares levels of pollutants and physical variables at the time of presentation for headaches to corresponding levels on preceding and subsequent weeks (Tietjen et al., 2012).

Table 5 shows a resume of the statistical model results performance for two models (A, B and C). The first column of Table 3 presents the statistics tests most often used in generalized linear models and represent measures of dispersion (generalized and/or corrected), which permit to test the quality of models. Values from Table 4, confirm that model A is the one with best performance results shown by statistical tests. These statistics tests are obtained using all the deviations obtained between the estimated and recorded (residuals) for each observation. Considering the Akaike Information Criterion, the objective is to minimize AIC. From the three models, model A is the one with lowest AIC, which means that evidence for the model A is the best compare with Model B and C. The same can be concluded when analysing AICC (Akaike Information Criterion corrected by minimizing the number of model parameters). When comparing with the quantile of a chi-square distribution with n-p degrees of freedom (n-number of observations, p-number of estimated parameters) it is possible to measure the suitability of models Results of deviance show that the three are suitable. Another measure of goodness of fit is the Pearson chi-square test, which leads to the same conclusions when compared with the quantile of the chi-square distribution with n-p degrees of freedom. Table 6 shows the likelihood ratio chi-square test, which compares each model with the null model. Regardless of model A is considered the best, each model individually, has a greater explanation of the dependent variable using some of the explanatory than any other model without explanatory variables.

Table 5. Resume of model's results performance.

| **Goodness of Fit**[a] | T min | T med | T max |
|---|---|---|---|
| Deviance | .000 | .001 | .000 |
| Scaled Deviance | 11.000 | 11.000 | 11.000 |
| Pearson Chi-Square | .000 | .001 | .000 |
| Scaled Pearson Chi-Square | 11.000 | 10.989 | 11.016 |
| Log Likelihood [b] | -1.958 | 12.967 | 6.718 |
| Akaike's Information Criterion (AIC) | 5.916 | 43.934 | 8.564 |
| Finite Sample Corrected AIC (AICC) | | 223.934 | |
| Bayesian Information Criterion (BIC) | 30.293 | 47.515 | 12.941 |
| Consistent AIC (CAIC) | 41.293 | 56.515 | 23.941 |

Dependent Variable: RH min
Model: (Intercept), Headache, Feeling heavy headed, Dizziness, Skin rash itchiness, T min, $PM_{10}$min[a]

Dependent Variable: RH med
Model: (Intercept), Headache, Dizziness, Skin rash itchiness, T med, $PM_{10}$med[a]

Dependent Variable: RH max
Model: (Intercept), Headache, T max, Feeling heavy headed, $CO_2$max, $PM_{10}$max, Hoarse dry throat [a]

a. Information criteria are in small-is-better form.

b. The full log likelihood function is displayed and used in computing information criteria.

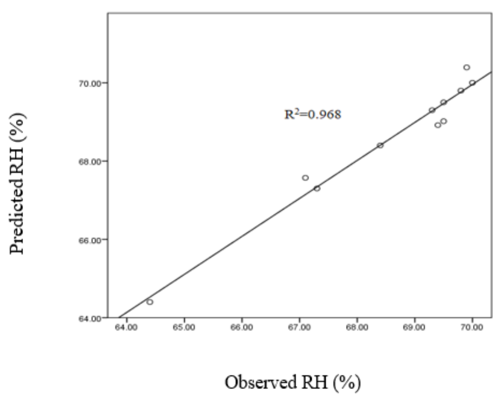
Table 6. Models' likelihood ratio chi-square test performance

| Model | Likelihood Ratio Chi-Square | df | Sig. |
|---|---|---|---|
| RH min | 8.399 | 9 | .000 |
| RH med | 22.001 | 7 | .003 |
| RH max | 30.057 | 9 | .000 |

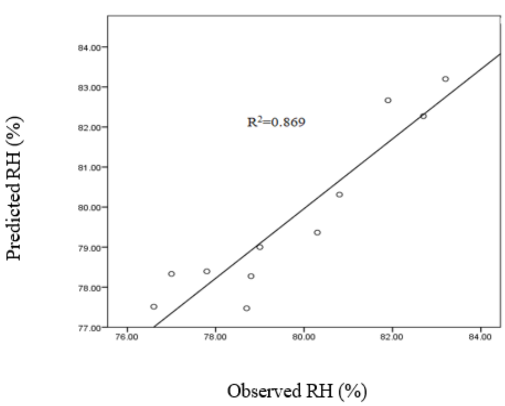
Dependent Variable: RH min
Model: (Intercept), Headache, Feeling heavy headed, Dizziness, Skin rash itchiness, T min, $PM_{10}$min[a]
Dependent Variable: RH med
Model: (Intercept), Headache, Dizziness, Skin rash itchiness, T med, $PM_{10}$med[a]
Dependent Variable: RH max
Model: (Intercept), Headache, T max, Feeling heavy headed, $CO_2$max, $PM_{10}$max, Hoarse dry throat [a]
a. Compares the fitted model against the intercept-only model.

Figure 2 shows the scattered plot with rh measures versus temperature values predicted by three models (A, B and C). The $R^2$ values for model A outstanding than model B due to the $R^2$ of model A ($R^2$= 0.968) higher than model B ($R^2$= 0.869) and C ($R^2$= 0.935). The calculation of $R^2$ showed that model A was the best fitted model with $R^2$=96.8%.

a)




b)




c)

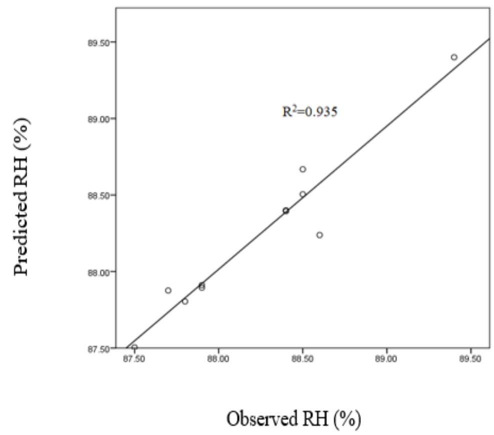



Figure 2. Model Validation.

a) Model A, b) Model B, c) Model C

## 4. CONCLUSION

In conclusion, this study showed that there were a few contributions od SBS and IAQ towards temperature inside the building such as dizziness, heavy headed, headache and itchiness, besides PM $_{10}$ and temperature. This study showed that Model A ($R^2$=96.8%) outstand Model B (86.9%) and Model C (93.5%). Results shows a good accuracy for situations. The model is important tool in situations where there are no measurements of relative humidity, but it is possible to achieve data from other gaseous air pollutants and SBS.

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