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MODELLING OF SICK BUILDING SYNDROME (SBS) SYMPTOMS AND INDOOR AIR QUALITY (IAQ) ACROSS DOMINANT SUB-ECONOMIES IN TERENGGANU: A STUDY OF MONSOONAL VARIATIONS

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Thesis Submitted in Fulfilment of the Requirement for degree of Doctor of Philosophy in the Institute of Tropical Biodiversity and Sustainable Development
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DEDICATION

Dedicated this thesis to:

My all: Abah & Mak.

My anchor throughout the storm & turbulence:

Professor Marzuki bin Hj. Ismail & Associate Professor Dr Samsuri Abdullah

I owe you guys, big time

Thanks a lot

May Allah bless

Abstract of thesis presented to the Senate of Universiti Malaysia Terengganu in fulfilments of the requirements for the degree of Doctor of Philosophy

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Optimum indoor air quality (IAQ) is crucial for maintaining a healthy work environment. This study examines the effects of IAQ on Sick Building Syndrome (SBS) symptoms across various economic subsectors during the monsoonal seasons in Terengganu, Malaysia. Four locations representing the education (S1), wholesale or retail trade (S2), manufacturing (S3), and services (S4) subsectors were assessed. IAQ was measured using ventilation indicators (carbon dioxide, CO_2), chemical parameters (formaldehyde (HCHO), total volatile organic compounds (TVOC), and carbon monoxide (CO)), and physical parameters (temperature, relative humidity, air movement) during the Southwest Monsoon (SWM) and Northeast Monsoon (NEM). The objectives included evaluating IAQ compliance, simulating 3D distributions using Computational Fluid Dynamics (CFD), identifying IAQ factors through Principal Component Analysis (PCA), and developing predictive Generalized Linear Models (GLM). Data included SBS symptom feedback and IAQ metrics, analysed using GLM with SBS syptoms as the dependent variable. Results showed seasonal IAQ variations, with temperatures ranging from 23.50°C to 32.91°C and relative humidity from 57.77% to 90.68%. CO_2 levels were higher in enclosed spaces, particularly in manufacturing and retail sectors during the SWM. CFD simulations revealed increased turbulence near ventilation systems, with accuracies of up to 91.90% (SWM, S1) and 91.17% (NEM, S4). PCA identified three main IAQ contributors: physical conditions, chemical exposure, and human activities, accounting for up to 45.58% (NEM, S3), 24.17% (SWM, S3), and 31.42% (SWM, S4) of variance. The GLM demonstrated higher predictive accuracy during the NEM, with an R^2 of up to 0.9949. Seasonal variations in IAQ significantly impacted SBS symptoms across different economic sectors in Terengganu, Malaysia. Poor IAQ, driven by physical conditions, chemical exposures, and human activities, was found to be worse during the SWM. The study recommends improving ventilation in enclosed spaces, regularly monitoring IAQ to address seasonal changes, reducing chemical emissions, controlling indoor activities, and enforcing IAQ compliance to create healthier work environments.

Abstrak tesis yang dikemukakan kepada Senat Universiti Malaysia Terengganu sebagai memenuhi keperluan untuk Ijazah Doktor Falsafah

PEMODELAN GEJALA SINDROM BANGUNAN SAKIT (SBS) DAN KUALITI UDARA DALAMAN (IAQ) MERENTASI SUB-EKONOMI DOMINAN DI TERENGGANU: KAJIAN VARIASI MONSUN

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Kualiti udara dalaman (IAQ) yang optimum adalah penting untuk mengekalkan persekitaran kerja yang sihat. Kajian ini meneliti kesan IAQ terhadap gejala Sindrom Bangunan Sakit (SBS) merentasi pelbagai subsektor ekonomi semasa musim monsun di Terengganu, Malaysia. Empat lokasi yang mewakili subsektor pendidikan (S1), perdagangan borong atau runcit (S2), pembuatan (S3), dan perkhidmatan (S4) telah dinilai. IAQ diukur menggunakan indikator pengudaraan (karbon dioksida, CO_2), parameter kimia (formaldehid (HCHO), jumlah sebatian organik meruap (TVOCs), dan karbon monoksida (CO)), serta parameter fizikal (suhu, kelembapan relatif, pergerakan udara) semasa Monsun Barat Daya (SWM) dan Monsun Timur Laut (NEM). Objektif kajian termasuk menilai pematuhan IAQ, mensimulasikan taburan 3D menggunakan Dinamik Bendalir Komputasi (CFD), mengenal pasti faktor IAQ melalui Analisis Komponen Utama (PCA), dan membangunkan Model Linear Umum (GLM) ramalan. Data yang digunakan termasuk maklum balas gejala SBS dan metrik IAQ, dianalisis menggunakan GLM dengan SBS sebagai pemboleh ubah bersandar. Keputusan menunjukkan variasi IAQ bermusim, dengan suhu antara 23.50°C hingga

32.91°C dan kelembapan relatif antara 57.77% hingga 90.68%. Tahap CO_2 adalah lebih tinggi di ruang tertutup, terutamanya dalam sektor pembuatan dan runcit semasa SWM. Simulasi CFD mendedahkan peningkatan pergolakan berhampiran sistem pengudaraan, dengan ketepatan sehingga 91.90% (SWM, S1) dan 91.17% (NEM, S4). PCA mengenal pasti tiga penyumbang utama IAQ: keadaan fizikal, pendedahan kimia, dan aktiviti manusia, yang menyumbang sehingga 45.58% (NEM, S3), 24.17% (SWM, S3), dan 31.42% (SWM, S4) daripada varians. GLM menunjukkan ketepatan ramalan yang lebih tinggi semasa NEM, dengan nilai R^2 sehingga 0.9949. Variasi bermusim dalam IAQ memberi kesan ketara kepada gejala SBS dalam pelbagai sektor ekonomi di Terengganu, Malaysia. IAQ yang lemah, dipacu oleh keadaan fizikal, pendedahan kimia, dan aktiviti manusia, didapati lebih buruk semasa SWM. Kajian ini mencadangkan beberapa langkah seperti meningkatkan pengudaraan di ruang tertutup, memantau IAQ secara berkala untuk menangani perubahan bermusim, mengurangkan pelepasan bahan kimia, mengawal aktiviti dalaman, dan menguatkuasakan pematuhan IAQ untuk mewujudkan persekitaran kerja yang lebih sihat.

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APPROVALS

I certify that an Examination Committee has met on 15th September 2021 to conduct the final examination of Full Name, on her Doctor of Philosophy thesis entitled **"MODELLING OF SICK BUILDING SYNDROME (SBS) SYMPTOMS AND INDOOR AIR QUALITY (IAQ) ACROSS DOMINANT SUB-ECONOMIES IN TERENGGANU: A STUDY OF MONSOONAL VARIATIONS"** in accordance with the regulations approved by the Senate of Universiti Malaysia Terengganu. The Committee recommends that the candidate be awarded the relevant degree. The members of the Examination Committee are as follows:

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This thesis has been accepted by the Senate of Universiti Malaysia Terengganu in fulfilment of the requirement for the degree of Philosophy Science.

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DECLARATION

I hereby declare that the thesis is based on my original work except for quotations and citations which have been duly acknowledged. I also declare that it has not been previously or concurrently submitted for any other degree at UMT or other institutions.

AMALINA BINTI ABU MANSOR

Date:

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LIST OF ABBREVIATIONS

ACH	Automated cleaning house
AM	Air movement
API	Air Pollutant Index
AQMS	Air Quality Monitoring Station
ASHRAE	American Society of Heating, Refrigerating and Air-Conditioning Engineers
CFD	Computational Fluid Dynamics
CO	Carbon Monoxide
CO_2	Carbon Dioxide
COPD	Chronic Obstructive Pulmonary Disease
DOSM	Department of Statistics Malaysia
GLM	Generalized Linear Model
HCHO	Formaldehyde
IA	Index of Agreement
IAQ	Indoor Air Quality
ICOP	Industrial Code of Practice
MAE	Mean Absolute Error
NAE	Normalized Absolute Error
NEM	Northeast Monsoon
PCA	Principal Component Analysis
PCs	Principal Components
PM	Particulate Matter
R^2	Coefficient of determination
RH	Relative Humidity
RMSE	Root Mean Square Error
RSP	Respirable Suspended Particulates
SBS	Sicks Building Syndrome
SDG	Sustainable Development Goals
SWM	Southwest monsoon
T	Temperature

TVOC	Total Volatile Organic Compound
UN	United Nation
WHO	World Health Organization

CHAPTER 1

INTRODUCTION

1.1 Background of the Study

Indoor Air Quality (IAQ) has garnered significant attention in recent years, particularly in developing countries, where individuals spend approximately 90% of their time indoors, either at home or in the workplace (Mahmoud & Abdel-Salam, 2022). Studies have revealed that indoor air is often more contaminated than outdoor air, posing substantial risks to human health (Onwusereaka *et al.*, 2022). IAQ assessments have become a crucial topic for both residential and office environments due to the high concentrations of indoor air pollutants, especially considering the extended exposure time individuals experience indoors (Liu *et al.*, 2021; Zannoni *et al.*, 2021). Monitoring IAQ involves evaluating physical parameters such as air movement (AM), temperature (T), and relative humidity (RH), along with chemical pollutants like formaldehyde (HCHO), volatile organic compounds (VOCs), and carbon monoxide (CO) (Konstantinou *et al.*, 2022; Mu & Kang, 2022). Ventilation performance indicators like carbon dioxide (CO_2) and particulate matter (PM) are also critical for IAQ assessment (Sarkhosh *et al.*, 2021). Proper IAQ monitoring is essential to identify pollutant sources, evaluate potential health risks, and ensure compliance with recommended standard limits for building occupants' safety and comfort (Branco *et al.*, 2020).

Sick Building Syndrome (SBS) symptoms is a term used to describe adverse health effects linked to poor IAQ, where the specific sources of health issues remain unidentified. The term “syndrome” underscores the complexity of factors contributing to symptoms such as nose, eye, and throat irritation, skin rashes, fatigue, and headaches

(Lucialli *et al*., 2020). Prolonged exposure to poor IAQ can exacerbate these conditions, leading to severe health implications (Meng *et al*., 2021). Sources of SBS symptoms include biological contaminants, inadequate ventilation, chemical emissions from paints, cleaning products, and building materials, and environmental factors like temperature and humidity (Sadrizadeh *et al*., 2022; Tainio *et al*., 2021).

The effects of IAQ on SBS symptoms are particularly pronounced during monsoonal variations, as weather patterns significantly influence indoor environmental conditions. In Malaysia, the climate is shaped by the Southwest Monsoon (SWM) and the Northeast Monsoon (NEM), each presenting unique IAQ challenges (Abu-Rub *et al*., 2023; Berville *et al*., 2021). The SWM season (June to September) brings hot and dry weather with higher temperatures and lower humidity (Othman *et al*., 2023). These conditions can elevate indoor temperatures, increase pollutant evaporation rates, and reduce air movement. Poor ventilation during SWM results in a build-up of pollutants such as CO_2 and TVOC, exacerbating SBS symptoms like fatigue, drowsiness, and eye irritation (Branco *et al*., 2020; Salju *et al*., 2023). In contrast, the NEM season is characterized by cooler and wetter conditions with higher humidity and frequent rainfall (Meteorologi Malaysia, 2020). Increased moisture promotes the growth of mould, mildew, and dust mites, contributing to respiratory issues and allergic reactions (Branco *et al*., 2019; Capua *et al*., 2023). Reduced ventilation during this period intensifies indoor pollutant accumulation, further worsening SBS symptoms (Chawla *et al*., 2023).

Terengganu's economic activities are primarily concentrated in the agriculture, manufacturing, and services sectors, with services accounting for 52.7% of its GDP in 2021 (DOSM, 2022). Sub-economies like education, wholesale and retail trade, and hospitality involve indoor environments with varying IAQ challenges. For instance, classrooms often face high CO_2 levels, while retail spaces and hotels encounter fluctuating VOC levels due to cleaning agents and occupancy patterns (Fantozzi *et al*., 2022; Deng *et al*., 2024). Addressing IAQ in these environments is vital for enhancing productivity, occupant comfort, and overall economic efficiency (Lee *et al*., 2020). Table 1.1 presents the percentage share of different economic sectors to Terengganu's Gross Domestic Product (GDP) from 2019 to 2021, highlighting the region's economic composition and dynamics over this period. The services sector consistently accounted for the largest contribution, increasing from 50.3% in 2019 to 52.7% in 2021, underscoring its dominance in Terengganu’s economy. Within the services sector, wholesale and retail trade showed steady growth, rising from 16.6% in 2019 to 17.8% in 2021. The education sub-sector exhibited significant fluctuations, peaking at 19.9% in 2020, likely reflecting pandemic-related shifts in the education landscape, before decreasing to 15.3% in 2021. Similarly, hospitality, finance, insurance, and business services maintained stable contributions, hovering around 12%, while other services saw a gradual increase, reaching 8.6% in 2021. Meanwhile, the manufacturing sector demonstrated a declining trend, decreasing from 37.5% in 2019 to 34.9% in 2021. Agriculture showed a modest but consistent increase, contributing 8.6% by 2021. In contrast, mining and quarrying and construction sectors maintained relatively small shares, with minimal year-to-year variations. These statistics indicate a growing reliance on the services sector in Terengganu's economy, with implications for IAQ challenges due to the high concentration of indoor activities in service-related establishments. This highlights the importance of IAQ assessments in service-oriented spaces, such as retail shops, classrooms, and office buildings, to ensure a healthy and productive environment for occupants.

Table 1.1 Statistic of percentage share to Gross Domestic Product (GDP), Terengganu (2019-2021) (DOSM, 2022)

Type of economic sector	**2019**	**2020**	**2021**
Agriculture	8.2	8.4	8.6
Mining and quarrying	0.5	0.6	0.5
Manufacturing	37.5	36.4	34.9
Construction	3.3	3.2	3.2
Services	50.3	51.4	52.7
Wholesale and retail trade	16.6	17	17.8
Education	13.9	19.9	15.3
Hospitality, finance insurance, and business services	12.0	12.4	12.0
Other services	8.0	8.0	8.6
Plus: Import duties	0.2	0.0	0.1
Total percentages	**100.0**	**100.0**	**100.0**

Given the complex interplay of factors affecting IAQ, advanced modelling and analysis tools like Computational Fluid Dynamics (CFD), Principal Component Analysis (PCA), and Generalized Linear Models (GLM) are essential for comprehensive IAQ assessments. CFD provides precise spatial mapping of pollutant dispersion, offering insights into real-world indoor air conditions without assumptions (Geng *et al*., 2023). PCA helps identify critical pollutant sources and patterns, while GLM is effective for predicting pollutant levels and their health implications using count data (Ahlmann-Eltze & Hube, 2021). Together, these methodologies enhance our understanding of IAQ dynamics, support regulatory compliance, and contribute to achieving Sustainable Development Goals (SDG), particularly Goal 3, which aims to promote health and well-being for all.

Sustainable Development Goal 3 (SDG 3), established by the United Nations in 2015, aims to "ensure healthy lives and promote well-being for all at all ages." This goal is particularly relevant in addressing the challenges associated with IAQ and its implications for SBS symptoms. With most people spending a significant portion of their time indoors, especially in spaces like schools, offices, and healthcare facilities, maintaining high IAQ is critical to achieving SDG. Indoor air pollutants (IAP), such as PM or also known as respirable suspended particulate (RSP), VOCs, and other gaseous pollutants, can significantly impact occupants' health, leading to respiratory issues, allergies, and other chronic illnesses. Poor IAQ disproportionately affects vulnerable groups, including children, the elderly, and those with pre-existing health conditions. By aligning IAQ standards with SDG 3, regulatory frameworks like the Industrial Code of Practice for Indoor Air Quality (ICOP-IAQ 2010) provide baseline data to evaluate and manage pollutant levels in indoor spaces, ensuring environments conducive to health and well-being.

SBS symptoms emphasize creating environments that support the health, safety, and productivity of their occupants while reducing environmental impact. IAQ plays a crucial role in ensuring that indoor environments promote physical and mental well-being. Effective IAQ management in sustainable buildings fosters healthier occupants, enhances cognitive function, and supports a higher quality of life which all core principles of SDG 3. The adoption of advanced tools, such as CFD models, aligns with

SDG 3 by offering precise and scenario-specific IAQ assessments. Unlike basic spatial mapping models, CFD does not rely on assumptions, providing accurate real-world predictions of pollutant dispersion and concentration. These insights are essential for designing and regulating sustainable indoor environments that prioritize health. Workers, who spend a significant amount of time in classrooms, are particularly vulnerable to poor IAQ, which can reduce their working performances and productivity. High-quality IAQ in educational spaces ensures a conducive working environment for future leaders, directly supporting the well-being goals of SDG 3. Regulatory agencies can use spatial mapping and CFD modelling to implement policies that safeguard the health of this demographic.

The integration of IAQ management within the framework of SDG 3 underscores its significance in promoting health and well-being. Sustainable building practices that prioritize IAQ not only contribute to achieving SDG 3 but also create environments that support human development, productivity, and long-term sustainability. Addressing IAQ challenges is therefore critical to realizing the broader objectives of sustainable development and ensuring a healthier future for all.

1.2 Problem Statement

IAQ plays a crucial role in determining the comfort, health, and productivity of individuals in indoor environments. Poor IAQ is a major contributor to a range of health issues, including respiratory problems, cognitive impairment, and symptoms collectively known as Sick Building Syndrome (SBS) symptoms, such as fatigue, headaches, nausea, and difficulty concentrating. Industrial workplaces, where employees spend most of their time, are particularly vulnerable to poor IAQ. However, research on IAQ in Malaysia has primarily focused on educational, commercial, and healthcare buildings, with limited attention to industrial buildings (Nazli *et al.*, 2024; Ibrahim *et al.*, 2024). This gap exists partly due to access restrictions imposed by industrial facility owners, which hinder comprehensive evaluations of IAQ in these environments (Alwi *et al*., 2021).

Poor IAQ is driven by physical factors like high temperature, excessive humidity, and insufficient ventilation, as well as chemical pollutants such as carbon dioxide (CO_2), volatile organic compounds (TVOC), particulate matter (PM), and formaldehyde (HCHO). These factors often exceed acceptable levels indoors, where pollutant concentrations can be five times higher than outdoor levels (Li *et al*., 2024; Fang *et al*., 2022). Long-term exposure to such environments not only increases the risk of respiratory and cardiovascular diseases but also impairs cognitive functions, reduces worker productivity, and contributes to SBS symptoms (Jia *et al*., 2021; Huang & Liao, 2021). Poor IAQ is associated with stress and a significant decrease in problem-solving and decision-making capabilities when CO_2 levels exceed 600 ppm (Mucha *et al*., 2024). Furthermore, exposure to particulate matter and other airborne pollutants has been linked to higher rates of mortality and morbidity, underscoring the need for effective IAQ management (Hou *et al*., 2021; Sha *et al*., 2024).

Seasonal variations due to Malaysia's monsoonal climate add another layer of complexity to IAQ management. The East Coast of Peninsular Malaysia, including industrializing regions like Terengganu, experiences significant changes in temperature, humidity, and pollutant levels across different monsoons. These variations influence the indoor environment and exacerbate the challenge of maintaining acceptable IAQ (Rahim *et al*., 2023; Zaki & Bari, 2022). However, studies on how these monsoonal variations impact IAQ and SBS symptoms are limited, leaving a critical gap in understanding and mitigation strategies (Wan *et al*., 2024).

Socioeconomic factors further complicate IAQ management in industrial settings. Low-income sectors may lack the resources to implement effective ventilation and pollutant control systems, making workers more vulnerable to the adverse effects of poor IAQ (Yahaya *et al*., 2023). In contrast, high-income sectors might prioritize energy efficiency measures over ventilation quality, which can lead to suboptimal IAQ (Rahim *et al*., 2023). This disparity highlights the need for tailored IAQ solutions that address varying economic contexts while ensuring worker safety and productivity. Future trends in how different subdominant economies may affect IAQ could manifest in the following ways such as resource allocation and IAQ control. Low-income sectors can limit budgets may hinder the adoption of advanced IAQ technologies and proper maintenance of ventilation systems. This could lead to higher levels of pollutants (e.g.,

CO_2, particulate matter, and TVOC) in workplaces, particularly in manufacturing or retail spaces where worker density is high and natural ventilation is minimal. Besides that, high-income sectors can afford better IAQ systems, a focus on energy efficiency (e.g., sealing buildings to reduce heating/cooling costs) could inadvertently compromise ventilation, leading to pollutant buildup in enclosed spaces. Sectors like manufacturing often generate higher emissions from machinery, materials, or chemical processes, requiring advanced pollutant management. Without targeted interventions, such sectors will experience worsening IAQ. Service-oriented sectors (e.g., offices) may face IAQ issues from overcrowding, poor ventilation, and prolonged use of synthetic materials (furniture, flooring). Future challenges may include balancing worker comfort with energy-efficient building designs. Technological disparities such as low-resource economies may rely on outdated equipment and cheaper materials that emit higher levels of formaldehyde or VOCs, exacerbating IAQ issues. In contrast, high-resource economies could adopt smart IAQ systems with real-time monitoring, but their benefits might not extend to smaller enterprises within the same subsector. Rapid urbanization in low-income economies could increase IAQ problems due to overcrowding and poorly regulated construction practices. Monsoonal climates could exacerbate humidity and mould issues in inadequately ventilated spaces. High-income economies might mitigate some climate impacts but could still face challenges in balancing urban density with sustainable IAQ practices. Policy and compliance gaps showed that economic disparities can result in uneven enforcement of IAQ regulations. Low-income sectors may struggle to comply due to financial constraints, whereas high-income sectors might focus more on cost-saving measures like reduced ventilation, leading to hidden IAQ risks.

The complexity of IAQ and SBS symptoms lies in the interrelationship between multiple contributing factors, such as physical parameters (e.g., temperature, humidity, airflow), chemical pollutants (e.g., HCHO, TVOCs, CO_2), and ventilation efficiency. Multicollinearity among these variables often poses a significant challenge to identifying root causes and implementing effective mitigation measures (Mansor *et al*., 2024; Zhang *et al*., 2022). CFD is a powerful tool for modelling airflow and pollutant dispersion within buildings, enabling an understanding of how ventilation and interior layouts influence IAQ (Adelikhah *et al*., 2023; Zaeh *et al*., 2021). However, CFD simulations require integration with statistical methods to translate airflow dynamics into actionable insights.

Principal Component Analysis (PCA) addresses multicollinearity by reducing data dimensionality, identifying the primary contributors to poor IAQ, and simplifying the analysis of complex datasets (Saraga *et al*., 2024). Additionally, Generalized Linear Models (GLM) provide flexibility in modelling the relationships between IAQ parameters and SBS symptoms by accommodating mixed data types and various distributions (Albertin *et al*., 2023; Freihat & Al-Kurdi, 2023). These methods, when used in combination, can establish a robust framework for identifying the root causes of poor IAQ, predicting SBS risks, and informing targeted interventions.

Despite the proven utility of CFD, PCA, and GLM in IAQ research, their application to Malaysia's industrial buildings remains limited (Yahaya *et al*., 2023; Vita *et al*., 2023). This study aims to address these gaps by leveraging CFD simulations, PCA, and GLMs to evaluate the relationships between IAQ and SBS symptoms in Malaysian industrial settings, with a focus on the East Coast of Peninsular Malaysia. By incorporating monsoonal and socioeconomic variations into the analysis, this research will provide insights into the seasonal and economic dimensions of IAQ and SBS symptoms. These findings will help facility managers and policymakers implement evidence-based interventions, fostering healthier, more resilient work environments.

1.3 Aim and Objectives

The study aims to assess the IAQ with SBS symptoms inside buildings. The study embarks on the following objectives:

1. To determine the IAQ compliances in the study areas according to the Industrial Code of Practice Indoor Air Quality (ICOP-IAQ 2010) and trend demographic factors for SBS symptoms
2. To simulate the 3-Dimensional (3-D) distribution of real-world boundary IAQ parameters using Computational Fluid Dynamics (CFD)

3. To investigate the potential factors influencing IAQ using Principal Components Analysis (PCA) in Terengganu's key sub-economies
4. To develop Generalized Linear Models (GLM) that examine the relationship between SBS symptoms and IAQ parameters across dominant sub-economies in Terengganu.

1.4 Scopes of study

The scope of this study involves a comprehensive evaluation of IAQ and its impact on SBS symptoms in four dominant sub-economic sectors in Terengganu, Malaysia, under the influence of monsoonal variations. The focus areas, methodologies, and parameters are considered in this research. The study area focused on Terengganu, East Coast of Peninsular Malaysia, is characterized by distinct monsoonal climatic changes. Ventilation performance indicators were carbon dioxide and CO_2 (ppm). Chemical parameters consist of carbon monoxide, CO (ppm), formaldehyde, HCHO (ppm), total volatile organic compounds, TVOC (ppm), and respirable suspended particulate, RSP also known as particulate matter, PM (mg/m^3). The physical parameters included relative humidity, RH (%), temperature, T (^{0}C), and air movement. This study was conducted during the working day, and data were collected inside the building. Data was collected during the Southwest and northeast monsoons, each lasting ten days. A one-day pilot test was also undertaken in the research locations. The economy of Terengganu was primarily driven by two dominating sectors: manufacturing, which consists of one subsector, and services, which consists of three subsectors. The study areas chosen were Mset Inflatable Composite Corporation Sdn Bhd (subsector: transport equipment, others manufacturing and repairs), Raia Hotel & Convention Centre Terengganu (subsector: hospitality/accommodation), Tunas Manja Group Mart (TMG Mart) (subsector: wholesale and retail trade), and the control area, which is Sekolah Kebangsaan Tanjung Gelam (subsector: education). These sectors were chosen to represent various levels of socioeconomic development and building typologies in the region.

The sampling duration for every study area ranged from seven to eight hours, starting at 0800 hours and ending at 1700 hours, depending on consent from the premises. The readings were recorded at five or ten-minute intervals, depending on the suitability of each research area. The readings were carried out every hour. Based on the ICOP-IAQ (2010), instruments were placed at a height between 75 and 120 cm from the floor (Mansor *et al.*, 2021). Seasonal Sampling for data collection across different monsoon seasons for comparative analysis. Identification of IAQ parameters and pollutant sources with the highest impact on SBS symptoms was one of the expected outcomes. Understanding the role of monsoonal variations in influencing IAQ and health outcomes. Development of evidence-based strategies for improving IAQ and reducing SBS symptoms, tailored to the economic context and climatic challenges of Terengganu. Questionnaires were distributed to the staff or workers in the monitored premises. All building occupants from the selected sectors in Terengganu was selected. The questionnaire comprises four sections encompassing general information, background factors, occupational nature, previous or past three-month symptoms, present symptoms, and respondents' opinions about their workplace environment. The questionnaire was included in Appendix A. The general information consists of the name of the building or company and the department or division. The questionnaire in this section also asks whether your company has conducted any assessments for indoor air quality (IAQ). The background factors include the respondent's gender (male or female), age (categorized as less than 25 years, 25-39 years, 40-55 years, or over 55 years), and smoking status (with options of yes, no, or sometimes). Respondents were asked to give the duration of their services in terms of years and months and the duration of daily work hours at the respondent's primary workplace. The environmental condition section encompasses inquiries regarding the type of workstations, which might be enclosed rooms or open concepts. The inquiries inquire about the number of individuals that use your workstations and the type of air conditioning in your area, whether it is a central or split unit.

Analysis of how seasonal climatic changes (e.g., Northeast Monsoon (NEM) and Southwest Monsoon (SWM)) influence IAQ and SBS symptoms. Parameters considered consist of changes in external temperature and humidity besides effects of monsoon-driven pollutant dispersion and infiltration by evaluating the indoor-outdoor

(I/O) ratio. The study utilizes advanced computational and statistical tools to analyse IAQ and its relationship with SBS symptoms. PCA is used to identify key IAQ parameters contributing to poor air quality and SBS symptoms and to reduce data dimensionality while preserving essential trends and patterns. Next is CFD which simulates airflow and respirable suspended particulates (RSP) dispersion within the indoor spaces and evaluates ventilation efficiency and pollutant hotspots under varying monsoonal conditions. The last analysis was the GLM which quantifies the relationship between IAQ parameters and the occurrence of SBS symptoms and accommodates different types of data distributions and variables.

By integrating advanced tools like PCA, CFD, and GLM, this study seeks to provide actionable insights into mitigating IAQ issues and improving the well-being and productivity of building occupants in diverse economic sectors.

1.5 Significance of study

Optimal IAQ is crucial for maintaining a healthy environment within buildings. It creates a conducive and efficient environment for individuals residing in a building, providing them comfort, good health, and overall well-being. Excellent air quality improves worker productivity. Previous studies have also proved that occupants working in buildings with acceptable air quality experience lower symptoms associated with poor air quality Indoor air quality monitoring benefits the occupant's Early detection can alert the occupants to take precautionary measures, such as improving indoor activities and reducing sources of indoor pollution (Abouleish, 2021). These actions can help prevent short or long-term air pollution-related diseases like cardiopulmonary disease and asthma. Most people work to survive, and a convenient workplace is compulsory (Dominguez-Amarillo *et al.*, 2020). Failure to follow indoor air pollution (IAP) standards can be mitigated by implementing a schedule (Cheek *et al.*, 2021). Occupants can effectively minimize their exposure to pollutants in their buildings or workplaces by being aware of activities that cause IAP levels to exceed acceptable limits (Chojer *et al.*, 2020). It is crucial to monitor indoor air quality to establish baseline data for occupants (Jo *et al.*, 2020). For example, one way to protect workers from pollutants is to minimize exposure time by scheduling maintenance or cleaning tasks when other building occupants are absent (Gawande *et al.*, 2020). Another approach is to reduce the amount of chemicals used by or near workers, such as limiting the quantity used during maintenance or cleaning activities (Kumar *et al.*, 2023). Additionally, controlling the location of chemical use can be effective, such as performing maintenance work on moveable equipment in a maintenance shop rather than in the general area or placing equipment like printers and copiers in a separate room (Lee *et al.*, 2020). This study was particularly significant in the context of education. Educating building occupants about IAQ is crucial (Megahed & Ghoneim., 2021). Providing occupants with information regarding the sources and impacts of pollutants that they can control, as well as guidance on the correct operation of the ventilation system, can assist workers in becoming aware and taking measures to minimize their exposure (Mendoza *et al.*, 2021).

SBS symptoms associated with inadequate IAQ vary depending on the specific type of contaminant present (Mata *et al.*, 2022). These symptoms can be readily confused with symptoms of other ailments, such as allergies, stress, colds, and influenza. A typical indication is that individuals experience discomfort when within the premises, and their symptoms subside immediately after exiting the building or spending significant time away from it (for example, during weekends or vacations (De Capua *et al.*, 2023; Chojer *et al.*, 2020). Health or symptom surveys, such as the one provided in Appendix A, have been utilized to determine the presence of indoor air quality (IAQ) issues (Saini *et al.*, 2020). Inadequate and delayed response by building owners and operators to IAQ issues can result in various detrimental health effects. The health consequences of IAQ can manifest immediately upon exposure or several years later (Nimlyat *et al.*, 2023). Possible symptoms encompass ocular, nasal, and throat irritation, headaches, dizziness, rashes, muscle soreness, and exhaustion. Asthma and hypersensitivity pneumonitis are diseases associated with poor IAQ. The kind and severity of health impacts arising from poor IAQ are influenced by the specific pollutant, the exposure concentration, and the frequency and length of exposure (Both age and other medical disorders, such as asthma and allergies, can significantly impact the intensity of the effects Prolonged exposure to indoor air pollution (IAP) can have severe consequences for health, such as respiratory disorders, heart disease, and cancer, which can be highly incapacitating or even deadly (Saini *et al*., 2020).

The assessment of IAQ and SBS symptoms in four dominant sub-economies in Terengganu based on monsoonal variation using PCA, CFD, and GLM is a critical investigation that addresses pressing concerns surrounding human health, environmental sustainability, and economic productivity. The study's focus on integrating advanced tools and accounting for monsoonal variation uniquely positions it to provide valuable insights into managing IAQ in dynamic environmental contexts. First by enhancing public health and well-being. Indoor air pollution and its associated effects on human health are a growing concern, particularly in regions like Terengganu, where climatic variations can exacerbate exposure risks. Poor IAQ is directly linked to conditions such as respiratory disorders, cardiovascular diseases, and SBS symptoms, which negatively affect occupants' physical and mental health (Sa *et al.*, 2022; Settimo *et al.*, 2020). By systematically assessing IAQ and its impact on SBS symptoms across different sub-economies, this study provides actionable insights into mitigating health risks, directly aligning with Sustainable Development Goal 3 (Good Health and Well-being) (Nair *et al.*, 2022; Megahed & Ghoneim., 2021).

In addition, this study also addressing monsoonal variability and regional dynamics. Terengganu's distinct monsoonal variations significantly influence IAQ due to changes in temperature, humidity, and ventilation patterns (Susanto *et al.*, 2021). Understanding these seasonal dynamics is critical for designing tailored interventions that ensure consistent indoor air quality year-round (Cheek *et al.*, 2021; Sakellaris *et al.*, 2021). The study's emphasis on monsoonal impacts enhances the relevance of its findings for climate-sensitive regions, offering a template for adapting IAQ management strategies to diverse environmental conditions. The integration of cutting-edge methodologies like PCA, CFD and GLM ensures a robust, data-driven approach to assessing IAQ. PCA simplifies complex IAQ datasets, identifying key factors that contribute to air quality variations across different sub-economies. CFD provides detailed simulations of pollutant dispersion, offering high-precision insights that surpass traditional models and GLM enables the development of predictive models to evaluate the relationship between IAQ variables, monsoonal factors, and health outcomes. This combination of tools not only ensures accuracy but also provides policymakers and stakeholders with practical solutions for sustainable IAQ management.

This study was significant as one of economic and workplace productivity benefit. Improved IAQ directly impacts economic productivity by reducing absenteeism, enhancing cognitive performance, and mitigating health-related disruptions (Licina & Yildirim., 2021; Mentese *et al.*, 2020). Workers and students, who spend significant portions of their time indoors, are particularly vulnerable to the effects of poor IAQ. This study highlights the importance of maintaining high-quality IAQ in workplaces and educational institutions, ensuring environments conducive to productivity and learning. Such measures are essential for fostering long-term economic growth and well-being in Terengganu's sub-economies (Agarwal *et al.*, 2021; Fu *et al.*, 2021).

This research aligns with several Sustainable Development Goals (SDG) which involves SDG 3 (Good Health and Well-being) by reducing health risks associated with poor IAQ and promoting sustainable building practices, the study directly supports the goal of ensuring healthy lives. Secondly, SDG 11 (Sustainable Cities and Communities) which the findings from this study contribute to developing safer and more sustainable urban environments in Terengganu. By providing region-specific insights, the study equips policymakers and building operators with the tools needed to implement effective IAQ standards. These insights are critical for developing guidelines that account for Terengganu’s unique environmental and socioeconomic factors, ensuring that sub-economies are resilient to both seasonal and long-term challenges.

Advancing scientific knowledge as one of the significant of the study. This research fills critical gaps in understanding how monsoonal variations influence IAQ and SBS symptoms, particularly in tropical and subtropical regions like Terengganu. The innovative application of PCA, CFD, and GLM offers a replicable framework for future studies in other regions with similar climatic challenges, contributing to the global body of knowledge on sustainable IAQ management.

This study is highly significant as it integrates advanced modelling techniques with regional and climatic considerations to address a pressing public health and environmental issue. Its findings have the potential to improve the quality of life for building occupants, support economic growth, and advance the realization of sustainable development objectives. By addressing IAQ challenges in Terengganu's sub-economies, the research contributes to a healthier, more productive, and sustainable future.

1.6 Thesis Outline

This thesis is organized as follows. Chapter 1 covers the background of the study, problem statement, aim and objectives, scope of study, significance of the study, and conceptual framework.

In Chapter 2, a review of the literature is presented. The discussion includes a brief background of IAQ in Malaysia, including the introduction of IAQ and literature searches, which include the conclusion of the outputs from previous studies to enhance the importance of IAQ towards occupants or workers in Malaysia. This chapter also discusses the potential effects of indoor air pollutants, which can lead to SBS symptoms, and briefing about air pollutants such as RSP, CO_2, HCHO, CO, and TVOC. The relationship between IAQ and SBS symptoms is also discussed in the review, including any past literature related to previous statistical methods for forecasting indoor air pollutants.

The third chapter of this thesis (Chapter 3) presents the framework based on the study area, data analysis, which consists of pre-processing data collection and each phase in data analysis, which includes determining the trend of indoor air pollutants (IAP) and SBS symptoms with PCA, CFD, besides developing and validating a GLM.

Chapter 4 presents the findings and discusses the results obtained from the analyses, including demographic factors and trends of indoor air pollutants to determine compliances of air pollutants in the stud areas, which is known as descriptive analysis, then proceeds with simulation of indoor air pollutants inside the study areas using CFD. The result proceeded with PCA outputs, and last but not least were GLM results, which gave more understanding of the relationship between IAP and SBS symptoms. All the results are explained, along with justifications for the findings.

Lastly, Chapter 5, Conclusion and recommendations discusses the study's overall conclusion, including its significance and implications.

CHAPTER 2

LITERATURE REVIEW

2.1 Indoor Air Quality

IAQ refers to the condition of the air within industrial and workplace environments, specifically concerning the health, comfort, and safety of employees (Vardoulakis *et al.*, 2020). It encompasses the ventilation performance indicators and physical and chemical parameters. Indoor temperature should be maintained within recommended ranges to ensure thermal comfort and prevent extreme conditions that affect worker performance and health (Campagna & Desai, 2019). The relationship between SBS symptoms and IAQ is significant, as the quality of the air inside a building directly influences the health and comfort of its occupants (Sun *et al.*, 2019). IAQ is determined by a combination of physical and chemical parameters and the performance ventilation indicator (Aziz *et al.*, 2023). When these factors are not properly managed, they can contribute to the development of SBS symptoms, where building occupants experience a range of acute symptoms that often improve once they leave the building (Niza *et al.*, 2023). Workers across different sub-economy sectors experience varying exposure to indoor air pollutants and conditions based on their work environments and activities (Mentese *et al.*, 2020). Effective indoor air quality management, including proper ventilation, pollutant control, and temperature and humidity regulation, is essential to ensure worker health and comfort in each sector (Hou *et al.*, 2021). Tailoring IAQ strategies to the unique needs of each sector helps mitigate health risks and improve overall workplace conditions.

Physical parameters

Indoor temperature plays a crucial role in occupant comfort. When temperatures are too high or too low, they can cause discomfort, leading to symptoms such as headaches, fatigue, and difficulty concentrating (Jia *et al.*, 2021; Lim *et al.*, 2015). For example, a hot environment can make people feel lethargic, while a cold environment can lead to physical discomfort and distraction, both of which contribute to the overall feeling of being unwell (Lolliet *et al.*, 2022). Humidity levels should be controlled to avoid discomfort and issues such as mould growth or excessive dryness, typically within the range of 40-60% relative humidity (Lu *et al.*, 2018). Adequate air circulation, or called air movement, is required to prevent stagnant air and ensure that fresh air is distributed throughout the workspace (Blanco *et al.*, 2023). Humidity levels also significantly impact comfort and health. Low humidity can dry out the skin, eyes, and mucous membranes, leading to symptoms like dry skin, itchy eyes, and throat irritation (Awada *et al.*, 2022). Conversely, high humidity can create an environment conducive to dust mites, which are known to cause allergic reactions and respiratory issues such as coughing, sneezing, and shortness of breath (Altendorf *et al.*, 2023). These conditions contribute to the development of SBS symptoms by creating an indoor environment that is physically uncomfortable and potentially harmful (Garg *et al.*, 2022). Inadequate air movement can cause areas of stagnant air, where pollutants and contaminants can accumulate (Canceicao *et al.*, 2018). This leads to symptoms like headaches, dizziness, and feelings of stuffiness or discomfort (Chirico *et al.*, 2017). Proper air circulation is crucial for dispersing pollutants and maintaining comfort. Conversely, excessive air movement can create drafts, leading to discomfort such as chills, dryness, and irritation, contributing to symptoms like dry skin and respiratory irritation (Kumar *et al.*, 2022). Extreme temperatures can cause discomfort and stress, leading to symptoms such as headaches, fatigue, and difficulty concentrating (Kakoulli *et al.*, 2018). High temperatures can make occupants feel lethargic, while low temperatures can cause physical discomfort and distractions (Han *et al.*, 2015).

Chemical parameters

Chemical Parameters consist of CO, TVOC, HCHO, and PM, also known as RSP. CO levels should be controlled and maintained below-specified limits due to their toxic nature (Chirico *et al.*, 2017). Carbon monoxide is a colourless, odourless gas that can be extremely dangerous even at low concentrations. Exposure to CO can cause symptoms like headaches, dizziness, nausea, and in severe cases, impaired cognitive function and unconsciousness. Even low-level exposure over time can contribute to chronic SBS symptoms, such as fatigue and headaches. It is a gas that is produced when gasoline, diesel, or natural gas in car engines are not completely burned (Alkaabi *et al.*, 2023; Han *et al.*, 2015). According to previous studies, traffic-related outdoor sources account for the majority of indoor CO (Gomez-Acebo *et al.*, 2013). Thus, indoor concentrations are higher in buildings situated in naturally ventilated buildings and metropolitan locations (Lu *et al.*, 2018). Research on CO concentrations in workplace settings revealed an average range of 0.1 to 4.48 parts per million. According to a different study, urban areas have higher CO concentrations (4.48 ppm) than suburban (3.38 ppm) and rural (3.04 ppm) (Liu *et al.*, 2019). However, compared to urban regions (0.8 ppm), rural areas have greater CO levels (1.0 ppm) according to Pandya and Portnoy (2023). Due to its proximity to major roads and the infiltration of gas emissions from peak-time traffic congestion into buildings, the rural area had a high CO content (Mentese *et al.*, 2020).

TVOC levels should be monitored and kept within limits to reduce the risk of health issues associated with exposure to these chemicals. TVOCs are emitted from a wide range of indoor sources, including paints, cleaning products, adhesives, and office equipment (Lu *et al.*, 2015). High levels of TVOCs can lead to symptoms like headaches, dizziness, nausea, and irritation of the eyes, nose, and throat. Prolonged exposure can exacerbate these symptoms, leading to chronic discomfort and health issues (Othman *et al.*, 2023). Volatile organic compounds (VOC), which originate from both internal and external sources, are commonly found in school environments (Liu *et al.*, 2020; Snow *et al.*, 2019; Ghaffarianhoseini *et al.*, 2018). This chemical contaminant's presence is primarily associated with interior furnishings as well as other construction materials like paint, solvents, adhesives, carpets, fabrics, and textiles. In addition, wood-based products, which are used to make writing desks and cabinets, are one of the primary sources of volatile organic compounds (Salju *et al.*, 2023; Cheng *et al.*, 2021). Many toxicological consequences, both short- and long-term, such as headaches, weariness, drowsiness, and eye irritation, can result from exposure to airborne concentrations of VOC (Zainal *et al.*, 2019). It is not feasible to measure the amounts of particular chemicals due to the large range of possible sources and compositions (Wang *et al.*, 2024). To overcome this practical limitation, the idea of total volatile organic compound (TVOC) was developed. It offers a straightforward assessment of the total amount of volatile organic compounds without differentiating between different chemicals (Hong *et al.*, 2018). The amount of TVOC found outside may usually be regarded as insignificant because indoor concentrations of the gas are often higher than outside concentrations and have been rising over the last ten years (Piscitelli *et al.*, 2022). Some occupants may experience symptoms of irritation and discomfort in the 120–1200 ppb range (Wolkoff, 2018). These widespread symptoms can develop toxicity levels of up to 10,000 ppb. They can take on various shapes based on the species and degree of sensitivity of the residents (Subri *et al.*, 2024). Generally speaking, a maximum amount of 120 ppb is advised for the indoor environment to be deemed healthy (Hu *et al.*, 2017). Most nations view this level as a desirable goal and identify indoor environments with concentrations up to 1200 ppb as potentially dangerous (Sun *et al.*, 2019). According to Snow *et al.* (2019), some of the VOC compounds involved in these considerations will be extremely dangerous at very low concentrations. Hence, a broad approach is necessary. TVOC, which originate from both internal and external sources, are commonly found in school environments (Liu *et al.*, 2020; Snow *et al.*, 2019; Ghaffarianhoseini *et al.*, 2018). This chemical contaminant's presence is primarily associated with interior furnishings as well as other construction materials like paint, solvents, adhesives, carpets, fabrics, and textiles (Park *et al.*, 2019). In addition, wood-based products, which are used to make writing desks and cabinets, are one of the primary sources of volatile organic compounds (VOCs) (Cheng *et al.*, 2021)

Formaldehyde (HCHO) concentrations should be controlled to avoid irritation and potential long-term health effects, with specific limits set for safe exposure levels. Formaldehyde is a common indoor air pollutant found in building materials, furniture, and some textiles. It can cause significant irritation of the eyes, nose, and throat, leading to symptoms such as watery eyes, coughing, and respiratory distress (Salju *et al.*, 2023). One of the major sources of both indoor and outdoor air pollution is HCHO. Outdoor sources of HCHO emissions include transportation, burning biomass, biosphere, fuel combustion, and atmospheric reactions involving volatile organic compounds (VOCs) (Chen *et al*., 2022). HCHO can be found indoors in wood furniture that has been adhered to with formaldehyde-related adhesives. It can also form indoors due to chemical reactions and combustion (Salthammer, 2019). Numerous research has indicated that one of the main causes of indoor pollution is outdoor HCHO (Chen *et al*., 2018). Apart from indoor sources within the building, which are typically caused by powerful emission sources, outdoor HCHO is one of the sources of indoor pollution (Liu *et al.*, 2020; Chen *et al.*, 2022). Malaysia is among the developed and developing countries who's outdoor HCHO concentrations, as demonstrated by studies conducted from 2007 to 2015, typically varied from 1 to 5$\mu g/m^3$. (Liu *et al.*, 2020; Seguel *et al.*, 2016). Most of the sample set measured in industrialized and developing nations indicates that the median I/O HCHO concentration ranges from 0.17 to 0.4, suggesting that indoor environments do not significantly source outdoor HCHO (Sakar, 2019). The most popular technique for lowering the concentration of HCHO indoors is ventilation; however, ventilation from the outside can interfere with infiltration, and ventilation has a beneficial effect on reducing indoor pollutants but can also lead to overestimation (Sun *et al.*, 2019). The effect of outdoor HCHO concentration, which is normally taken to be equal to zero, on indoor environments has not been considered (Liu *et al.*, 2020). There is typically an inverse relationship between the air exchange rate and the formaldehyde levels in indoor air (Salthammer *et al.*, 2018). The tightness of buildings is said to drastically reduce the amount of fresh air available, which is why formaldehyde concentrations are higher (Tofful *et al.*, 2021). To understand the impact of outdoor HCHO, particularly on natural ventilation, across various spatial and temporal scales, it is necessary to keep in mind that a scenario in which all doors and windows are closed does not accurately reflect normal living conditions where people are moving around and opening and closing doors and windows regularly (Liu *et al.*, 2020; Hu *et al.*, 2017). RSP are tiny particles suspended in the air that can be inhaled into the lungs. These particles include dust, smoke, soot, and other fine particulate matter (Wolkoff *et al.*, 2018). RSPs can penetrate deep into the respiratory system, reaching the alveoli (the tiny air sacs in the lungs). This can cause or exacerbate conditions such as asthma, bronchitis, and other chronic respiratory diseases (Xiao *et al.*, 2021). Individuals with pre-existing respiratory conditions are particularly vulnerable. RSPs can trigger allergic reactions in sensitive individuals (Hassan *et al.*, 2021). Dust mites, spores, and other allergens besides vehicles often adhere to these particles, exacerbating allergic responses (Reuben *et al.*, 2019; Nezis *et al.*, 2022). Long-term exposure to high levels of RSPs has been associated with cardiovascular problems, decreased lung function, and, in severe cases, lung cancer (Zhang *et al.*, 2021; Mannan & Al Ghaudi, 2021). High levels of RSPs are associated with worsening symptoms of SBS symptoms by aggravating respiratory conditions and contributing to general discomfort (Mansor *et al.*, 2023; Blugseen *et al.*, 2020). Effective management of RSP through cleaning, ventilation, and air purification is essential for improving indoor air quality and reducing SBS symptoms (Fantozzi *et al.*, 2022; Ghaffarianhoseini *et al.*, 2018). RSP exposure can cause a variety of long- and short-term health effects, including an increase in respiratory symptoms, tissue alterations, a decrease in lung function, asthma, and early death (Mahmoud & Abdel-Salam, 2022; Zaman *et al.*, 2021; Oh *et al.*, 2019). Humans can be exposed to RSP by inhalation, which is one of the main ways that it can cause harm. The effects of particulate matter exposure depend on factors such as concentration, duration of exposure, and chemical makeup in addition to size (Mosallaei *et al.*, 2021). The air quality can be impacted by the presence of occupants, particularly in commercial buildings (Hattori *et al.*, 2022). Several factors, including poorly cleaned indoor surfaces, a high number of people crammed into a small space, low building floor-to-class ratios, inadequate ventilation, and resuspension particles on room surfaces, can influence the presence of particulate matter (Huo *et al.*, 2020). In addition to dust resuspension and intrusion from nearby roads, occupant activities inside the buildings also had an impact on the indoor-outdoor RSP ratio (Kumar *et al.*, 2023; Cheek *et al.*, 2021; Rasli *et al.*, 2021). The I/O ratio at schools is typically between 0.5-2.85, and a study conducted in Belgium revealed that there are significant differences in the I/O ratio with and without carpets, 2.63 and 1.03 (Chamseddine *et al.*, 2019).

Ventilation Performances indicator

The level of carbon dioxide (CO_2) should be kept within acceptable limits as an indicator of adequate ventilation and to prevent discomfort and cognitive impairment.

Elevated CO_2 levels are often an indicator of poor ventilation. High CO_2 levels are associated with symptoms such as headaches, drowsiness, and reduced cognitive function, which are common complaints in SBS symptoms. Poor ventilation also means that other indoor pollutants like TVOCs, CO, and formaldehyde are not effectively removed, further contributing to the development of SBS symptoms. CO_2 levels are often used as an indicator of the effectiveness of a building's ventilation system. High levels of CO_2 suggest that the ventilation system is not providing adequate fresh air, leading to a build-up of indoor pollutants. Elevated CO_2 levels can cause symptoms like headaches, dizziness, fatigue, and impaired cognitive function. These symptoms arise because high CO_2 levels often correlate with low oxygen levels, leading to a decrease in air quality and a corresponding increase in SBS symptoms. Currently, atmospheric air contains 300–700 parts per million of CO_2 (Mainka *et al.*, 2015). Within the room, the concentration of CO_2 rose, with gas equipment and living things serving as common sources. The amount of CO_2 that building inhabitants release is influenced by their food, physical activity, and general health (Tsantaki *et al.*, 2022). Naturally, the number of occupants and the inadequate make-up air supply were closely correlated with CO_2 concentrations, which also depended on the concentration of CO_2 in the outside air (Abdullah *et al.*, 2019; Zender *et al.*, 2019). The permitted indoor CO_2 content under the current IAQ standards was 1000 ppm, which was caused by the amounts of CO_2 in people's exhaled air (Susanto *et al.*, 2020). In the case of mechanical ventilation regulated by CO_2 sensors, 1000 ppm is typically defined as the maximum concentration of CO_2 (Oliveira *et al.*, 2019). In metropolitan areas, factors such as the number of occupants, ventilation rooms, room layouts, air exchange rates, and occupant activities in addition to outside activity can cause CO_2 levels to exceed 50–70% (Latif *et al.*, 2018; Morawska *et al.*, 2017; Leung *et al.*, 2015). The primary source of indoor air pollution is the occupier, as a result of exhalation from the workers or occupants the by-product is CO_2 (Snow *et al.*, 2019; Liu *et al.*, 2019). Apart from indoor activities that can raise CO_2 concentrations to 1356 ppm in schools, nurseries, or homes, the level of carbon dioxide in a well-ventilated building must range between 300-1000 ppm with a floor building mean of 800 ppm or less (Chen *et al.*, 2023; Stamatelopoulou *et al.*, 2019; Amoatey *et al.*, 2018). When combined with a moderate temperature and humidity level, complaints about indoor air quality can be lessened when there is less than 800 parts per million of CO_2. In addition to creating more frightening and dangerous situations, an inverse situation can lead to more complaints. When pupils are present, the amount of CO_2 in the classroom rises by 10% to 20% more than it does outside (Rodriguez *et al.*, 2022; Mainka *et al.*, 2018). In comparison to a typical setting, there was a 24% increase in mental stress and a 2.5-fold increase in physical stress due to excessive CO_2 production indoors (Jia *et al.*, 2021; Amoatey *et al.*, 2018). The indoor CO_2 level is typically higher than the outdoor level, indicating internal sources, with the tenant being the primary contributor (Chamseddine *et al.*, 2019; Zainal *et al.*, 2019).

Malaysian Indoor Air Quality Standard

Industrial Code of Practice on Indoor Air Quality needs to be effectively implemented, and companies must integrate these guidelines into their occupational health and safety management systems, ensuring continuous monitoring, regular assessments, and proactive measures to maintain a safe and healthy indoor environment. Examples of Standards and Guidelines consist of the American Society of Heating, Refrigerating and Air-Conditioning Engineers (ASHRAE) Standards, WHO Guidelines for Indoor Air Quality, and A (Occupational Safety and Health Administration) Guidelines. These are widely recognized guidelines for ventilation and IAQ, including ASHRAE Standard 62.1, which specifies minimum ventilation rates and IAQ standards for commercial buildings. WHO Guidelines for IAQ provides guidelines on various indoor pollutants, including recommendations on acceptable levels of common indoor air contaminants. Occupational Safety and Health Administration (OSHA) Guidelines were in the U.S., OSHA provides various guidelines and regulations concerning air quality in workplaces, particularly concerning exposure limits for hazardous substances. Workers in different sub-economy sectors experience varying exposures to indoor air pollutants and conditions. Wholesale and retail trades, education, and hospitality sectors each present unique challenges for IAQ management, impacting worker health and comfort in distinct ways. Addressing IAQ issues in these sectors involves tailored approaches to ventilation, pollutant control, and environmental conditions to promote a healthier working environment.

Act 514, the Occupational Safety and Health Act of 1994 (OSHA 1994), provides a framework for ensuring workplace safety and health in Malaysia. Although it primarily governs occupational safety and health, it can indeed be useful for guiding

IAQ management in workplaces. Act 514 establishes a broad regulatory framework for workplace safety and health, including aspects of indoor air quality. ICOP-IAQ 2010 provides specific guidelines and standards for managing IAQ, supporting the act's goals by offering practical measures for implementation. By adhering to both the act and the code of practice, employers can improve worker health, enhance productivity, and contribute positively to the economy. The focus on good IAQ leads to a healthier, more productive workforce, reduces costs related to health issues, and supports sustainable economic growth. As Table 2.1 illustrates, standards vary throughout countries and display a list of indoor pollutants together with acceptable levels. Malaysian Ministry of Human Resources Department of Safety and Health created the ICOP-IAQ, which was introduced in August 2010 and the standard widely used for practitioners and researchers to determine the air quality inside the building.

Table 2.1 Comparison Indoor Air Quality Standards and Guidelines

Categories	**Pollutants**	**ASHRAE**	**WHO**	**ICOP-IAQ**
Chemical	Carbon monoxide (CO)	[a]35 ppm	[b]10ppm	[a]10ppm
	Formaldehyde (HCHO)	[e]2ppm	[f]0.1mg/m^3	[a]0.1ppm
	Respirable particulate/ PM_{10}	[c]0.015mg/m^3	[c]0.045mg/m^3	[a]0.15 mg/m^3
	Respirable particulate/ $PM_{2.5}$	[c]0.035mg/m^3	[c]0.015mg/m^3	-
Physical	Air movement	[a]10L/s	[a]0.8 ft/s or 0.25m/s	[a]0.15-0.50m/s
	Temperature	[a]22.78-26.11^{0}C	[a]21-28^{0}C	[a]23-26 ^{0}C
	Relative Humidity	[a]30-60%	[b]30-65%	[a]40-70%
Ventilation Performance Indicator	Carbon Dioxide	[a]1000ppm	[a]1000ppm	[a]1000ppm

Notes:
[a] Exposure averaging time is 1 h
[b] Exposure averaging time is 8 h
[c] Exposure averaging time is 24 h
[d] Exposure averaging time is 1 year
[e] Exposure averaging time is 15 min
[f] Exposure averaging time is 30 min
[g] Exposure averaging time is 1 week
[h] Acute

2.2 Literature searches

The study gathered crucial data from reputable sources such as Google Scholar, Elsevier Bibliographic Database (SCOPUS), Science Direct, PubMed (MEDLINE), and Science Direct's electronic databases. This analysis encompasses articles published between 2017 and 2023. The study primarily examined the physical attributes, particle matter, and chemical air pollutants that are assessed in the indoor work setting. The database provided a total of 372 hits, with 294 from Scopus, 58 from Science Direct, and 20 from PubMed. Google Scholar revealed a total of 4,140 items, however, only the initial ten pages were examined, revealing six papers that were pertinent to the search. The final articles and the results of the database search were stored in an Excel spreadsheet**.**

2.2.1 Inclusion/Exclusion criteria

This evaluation includes only published research papers written in English, studies done in Malaysia, and papers that use quantitative data analysis. Only papers published after 2017 are included in the year of publication. Indoor air quality research started to garner attention in this year and will continue to do so until 2023, which represents the study's maturity year.

2.2.2 Paper screening and data extraction

Figure 2.1 illustrates the four stages of the paper review flow process. Following the completion of the searches, 372 titles and abstracts were screened to find research that satisfied the inclusion criteria. 85 articles were then eliminated from this list of 372 titles. By reading the title and abstract, the authors personally verified that the 67 articles satisfied the qualifying requirements. For the next procedure, a total of 42 publications about indoor air quality and sick building syndrome symptoms were included, whereas 16 papers that dealt with children and patients were removed. Following assessment, 4 papers were deemed irrelevant to the goal of the study and were not eligible for additional review and only 22 articles related to the objective of this study.

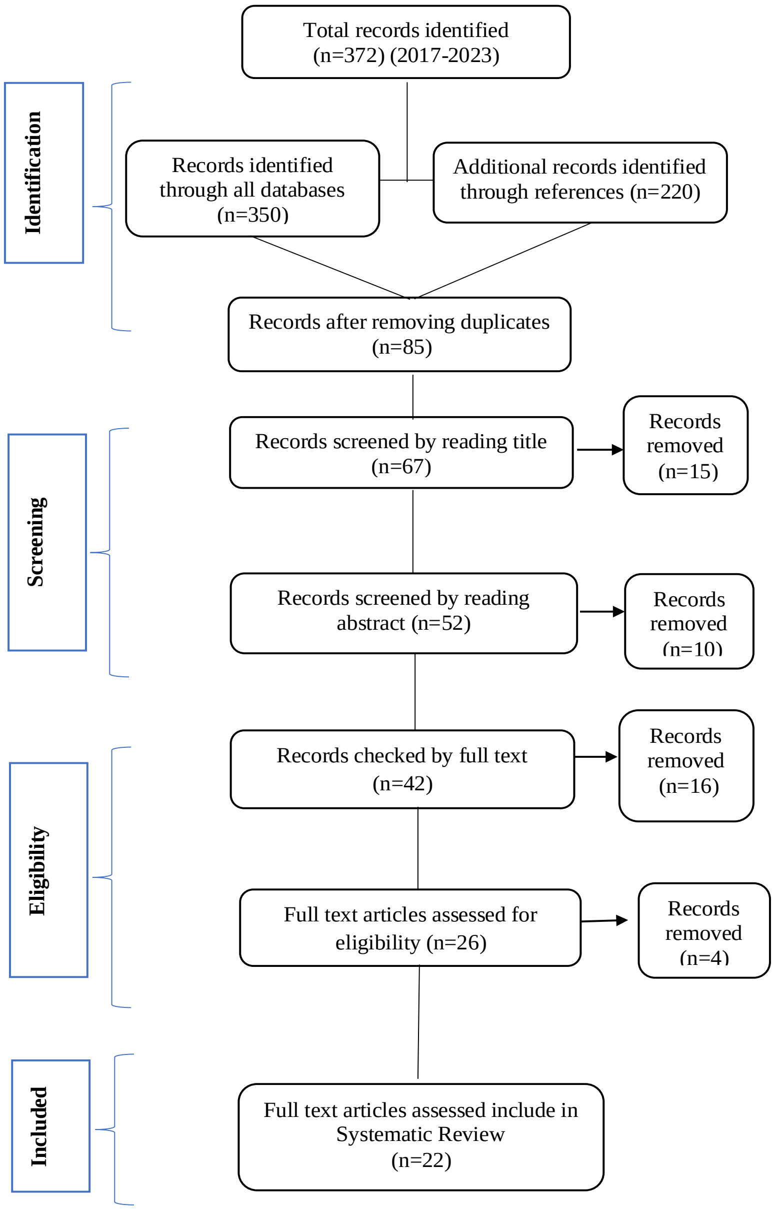


Figure 2.1 Stage of articles selection for IAQ and SBS symptoms

Previous studies were summarized in Table 2.2 which showed variations of air pollutants inside the buildings which can reduce the productivity of the occupants. This table provides a comprehensive summary of studies conducted between 2017 and 2023 in Malaysia that investigate the relationship between IAQ and SBS symptoms. It outlines the key findings from these studies, including the pollutants and IAQ factors that have been linked to SBS symptoms, the health impacts on building occupants, and the severity of symptoms reported. Additionally, the table highlights the research methodologies used, such as data collection methods, study settings (e.g., office buildings, schools, or residential areas), and sample sizes. This comparison helps to illustrate trends, gaps, and the current state of knowledge on how poor IAQ contributes to SBS symptoms in Malaysia, as well as the implications for public health and building management practices. There were 22 articles chosen for this study, as shown in Table 2.2 below. Of these, 11 were conducted in Kuala Lumpur or Selangor, 5 in Johor, 2 in Pulau Pinang, and 1 in each of the states of Terengganu, Kelantan, Pahang, and Melaka. Three (3) categories can be used to classify ventilation: 1. Area with open ventilation; 2. Area with full closed ventilation; and 3. Area with mixed ventilation. The primary indoor air quality issues in buildings (manufacturing, residential, educational, and office) that have been identified include particulate matter, carbon dioxide, temperature and humidity, and volatile organic compounds. Table 2.3 shows the output of each article. Out of the 22 articles reviewed, 5 were related to SBS symptoms and IAQ. Among these, only 1 article focused on an office setting, while the remaining 4 were conducted in educational environments. Table 2.2 summarizes research conducted in Malaysia from 2017 to 2023, focusing on the relationship between IAQ factors and the prevalence of SBSS in various indoor environments, including offices, educational institutions, and residential buildings.

IAQ regulation is necessary indoor air pollutants can be diluted when fresh outdoor air is brought into the space, whether through an air conditioning system or a natural ventilation system like a window (Cheng *et al.*, 2021). Unsatisfactory environmental conditions in classrooms, including insufficient ventilation, noise levels, and inadequate heating, have been documented since the mid-1990s (Bluyssen., 2020). The idea behind ventilation is to replace stale air with clean air. By installing interior ventilation, you may lessen the amount of outside air that enters your room. The major goal of using ventilation is to provide occupants with healthy air to breathe by removing and diluting contaminants that are already present in the air. As a result of the proper ventilation and building shielding installed for the residents' safety, indoor air quality should be superior to outdoor air quality. Nonetheless, interior air pollution concentrations are more than two thirds higher than outdoor concentrations (Cheek *et al.*, 2021; Napi *et al.*, 2021). High indoor readings have been linked to outdoor air quality, according to numerous studies. Three criteria determine how outside air enters an indoor space: infiltration, mechanical ventilation, and natural ventilation (Awang *et al.*, 2023; Othman *et al.*, 2022; Rodriguez *et al.*, 2022). Building leaks, fractures in the structure, and possible entry points beneath doors are all potential sources of infiltration (Rasli *et al.*, 2021; Snow *et al.*, 2019). The installation of an air conditioner and fan indicates mechanical ventilation. On the other hand, Liu *et al*., (2020) states that open doors and windows are considered natural ventilation, which allows pollutants to enter the building. Table 2.2 showed previous study of IAQ in Malaysia for past 7 years. Good IAQ contributes to a favourable environment for students, 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. 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. Therefore, it is important to determine the level of particles exposure, especially towards workers. Performance ventilation indicator, chemical and physical parameter was important to be measured to investigate how outdoor sources influence air flow inside the buildings. Approximately 67% of people work in non-agricultural, non-industrial indoor settings, which are referred to as indoor work environments. This means that nearly 70% of people are workers. Certain indoor environmental factors have been linked in scientific research to higher chances of nonspecific symptoms, respiratory disorders, and decreased performance (Norback *et al.*, 2021; Abdullah *et al.*, 2019(a)).

Table 2.2 presents the findings from various studies conducted in Malaysia between 2018 and 2023, highlighting key IAQ parameters, methodologies, and outcomes across different indoor environments. Several studies examined the link between IAQ and SBS symptoms in office buildings, where poor ventilation, high levels of VOC, and inadequate humidity control were commonly identified as contributing factors to SBS symptoms (Lu *et al.*, 2018). Research indicated that occupants in offices with inadequate ventilation and high levels of indoor pollutants were more likely to report symptoms such as headaches, eye irritation, and respiratory issues (Alias *et al.*, 2020). A significant study from 2019 found that improving ventilation and reducing indoor pollutant levels led to a marked decrease in reported SBS symptoms. Table 2.2 presents an overview of various studies conducted between 2017 and 2023 in Malaysia, examining the relationship between IAQ and SBS symptoms. The studies span different types of buildings, including educational, manufacturing, office, and hospital settings. The table highlights key factors, including the use of SBS symptoms questionnaires, the measurement of physical parameters (such as CO_2, temperature, and humidity), and IAQ parameters like CO_2, $PM_{2.5}$, PM_{10}, TVOCs, NO_2, HCHO, and CO. Most studies focused on educational buildings (16 studies), followed by manufacturing (5 studies), office (4 studies), and hospital (1 study). A majority of the studies used an SBS symptoms questionnaire to assess symptoms, though a few did not. CO_2 was frequently measured across many studies, followed by temperature and humidity. $PM_{2.5}$ and PM_{10} were often monitored, especially in educational and manufacturing buildings. TVOCs and NO_2 were also commonly measured in educational settings, while HCHO appeared in several studies. The research suggests that IAQ, particularly the levels of pollutants like CO_2, $PM_{2.5}$, and TVOCs, plays a significant role in the development of SBS symptoms, particularly in educational and manufacturing environments.

IAQ research also focused on schools and universities, exploring how classroom environments affect the health and well-being of students and staff. A 2021 study found that poor IAQ in educational institutions, characterized by high CO_2 levels and insufficient air exchange, was associated with increased reports of fatigue, headaches, and concentration difficulties among students. The study emphasized the importance of proper ventilation and the use of air purifiers to improve IAQ in educational settings.

Although less common, some studies also examined the relationship between IAQ and SBS symptoms in residential buildings, particularly in urban areas. A 2020 study highlighted the impact of indoor pollutants, such as formaldehyde and particulate matter, on the health of residents in high-density housing. The study found a correlation between poor IAQ and increased symptoms of SBS, particularly among children and the elderly.

Over the years, there has been a growing awareness of the importance of IAQ in preventing SBS symptoms. This has led to more studies focusing on identifying specific indoor pollutants and their health impacts. Some studies have explored the effectiveness of Malaysian IAQ guidelines and regulations in mitigating SBS symptoms, suggesting that stricter enforcement and updated standards could further reduce the prevalence of SBS symptoms. The majority of studies were conducted in urban centres, such as Kuala Lumpur, where indoor pollution and building density are higher. There is a noted gap in research focusing on rural areas.

Comparison of IAQ between old and new buildings which old building showed higher levels of NO_2 at 24.26 ppb, CO at 0.62 ppb, and PM_{10} at 4.99 $\mu g/m^3$ while new buildings had elevated levels of RH and ozone (O_3). Despite these differences, all IAQ measurements in both buildings complied with the standards set by the Department of Occupational Safety and Health (DOSH) even though there are slightly higher indoor pollutants at certain new buildings.

IAQ has a significant correlation with health effects, especially SBS symptoms. Linked to symptoms like dry hands, scalp itching, hoarse throat, headaches, eye issues, and nasal problems (p-value < 0.05) were related to the cooking technique. Children in schools located in industrial and urban areas are particularly vulnerable to injuries caused by air pollution. Temperature has a significant correlation with fatigue ($p = 0.036$) and dizziness ($p = 0.031$). Relative Humidity has correlated with dry, irritated eyes ($p = 0.047$), headaches ($p = 0.045$), and fatigue ($p = 0.040$). PM_{10} has a strong correlation with eye irritation ($p = 0.006$). Table 2.3 shows that previous studies illustrate various aspects of IAQ and SBS symptoms across different settings, employing a range of data analysis methods. The findings emphasize the importance of adequate ventilation, pollutant management, and environmental control to mitigate SBS symptoms and enhance overall indoor air quality.

Table 2.2 Overview of previous studies on the relationship Between Indoor Air Quality (IAQ) and Sick Building Syndrome (SBS) symptoms in Malaysia (2017-2023)

	Author	Types of Building	SBS Questionnaire	Physical parameter	IAQ monitoring Parameter besides physical parameter							
					CO_2	SO_2	NO_2	HCHO	TVOC	$PM_{2.5}$	PM_{10}	CO
1	Awang *et al.*, 2023	Educational	X	X		X	X			X	X	X
2	Nazli *et al.*, 2023	Manufacturing		X	X				X	X		X
3	Zaki *et al.*, 2022	Educational		X				X	X		X	
4	Azlan *et al.*, 2022	Educational	X	X	X						X	
5	Othman *et al.*, 2022	Educational			X					X	X	
6	Ezani *et al.*, 2022	Educational			X			X		X	X	
7	Ezani *et al.*, 2021	Educational			X					X	X	
8	Rasli *et al.*, 2021	Educational			X				X	X		X
9	Alwi *et al.*, 2021	Manufacturing						X	X	X	X	
10	Norback *et al.*, 2021	Educational	X		X		X	X	X			X
11	Fu *et al.*, 2021	Educational	X									
12	You *et al.*, 2023	Hospital			X						X	
13	Sarkhosh *et al.*, 2021	Office							X		X	
14	Idris *et al.*, 2020	Educational			X					X		
15	Khamis *et al.*, 2019	Office							X	X	X	
16	Nejat *et al.*, 2019	Manufacturing			X							
17	Zainal *et al.*, 2019	Office	X		X				X	X	X	X
18	Abdullah *et al.*, 2019	Educational			X			X	X	X		
19	Alias *et al.*, 2021	Educational					X	X		X		
20	Dzullkiflli *et al.* 2018	Manufacturing								X	X	X
21	Hasrunizzam *et al.*, 2018	Office			X		X		X			X
22	Hazrin *Et al.*, 2017	Educational		X		X				X		X

Table 2.3 presents a variety of studies conducted across Malaysia between 2018 and 2023, focusing on IAQ in different settings, from universities to schools, offices, and manufacturing areas. Common pollutants studied include $PM_{2.5}$, PM_{10}, CO, CO_2, NO_2, VOCs, O_3, temperature (T), relative humidity (RH), and air movement (AM). These studies reveal the diversity of IAQ issues in various environments, with some buildings exceeding acceptable limits for pollutants. Many studies noted the prevalence of SBS symptoms among workers and students, such as headaches, fatigue, eye irritation, and respiratory issues (Nazli *et al*., 2023; Azlan *et al*., 2022; Alwi *et al*., 2021). Specific environments like schools, universities, and manufacturing facilities showed correlations between poor IAQ and the occurrence of these symptoms. IAQ was evaluated in both indoor and outdoor environments, such as schools, offices, manufacturing facilities, and museums, with some studies comparing old and new buildings (Sarkhosh *et al*., 2021; Alwi *et al.,* 2021; Norback *et al*., 2021). For instance, old buildings had higher levels of pollutants like HCHO and CO compared to new ones (Yau *et al.,* 2023). Several studies used descriptive statistics, while others employed more advanced techniques like regression analysis, ANOVA, and correlation tests (Nazli *et al.,* 2023; Ezani *et al*., 2022; Fu *et al*., 2021; Abdullah *et al.,* 2019). These analyses helped to understand the relationships between pollutants, building characteristics, and health symptoms. Many studies assessed IAQ against established standards, such as those by the Department of Occupational Safety and Health (DOSH) and ASHRAE. Some studies found pollutants exceeding the recommended limits, particularly CO_2 in offices and $PM_{2.5}$ in schools near industrial areas (Khamis *et al.,* 2019; Dzulkifli *et al.,* 2018). Poor ventilation was often linked to elevated levels of CO_2 and PM, with activities like cooking, transportation, and high occupancy contributing to pollutant levels. Several studies emphasized the importance of ventilation systems in maintaining healthy IAQ (Zaki & Bari, 2022; Ezani *et al.,* 2021; Idris *et al*., 2020).

Overall, these findings highlight the importance of monitoring IAQ to prevent health issues related to poor air quality, particularly in environments with high occupancy or pollutant exposure. The studies also underline the need for improved ventilation and better building management to ensure compliance with IAQ standards.

Table 2.3 Summary of Findings from Previous Studies on Indoor Air Quality (IAQ) in Malaysia (2018-2023)

	Author	**Study Area**	**Data Analysis**	**Output**
1	Awang *et al.*, 2023	University $PM_{2.5}$, PM_{10}, O_3, RH, CO, SO_2, NO_2, T SBSS	Mann Whitney	The current investigation shows that the NO_2 (24.26 ppb), CO (0.62 ppb), and PM_{10} (4.99 µg/m^3) levels in the old building were significantly higher than those in the new building. However, the new building had noticeably higher RH and O_3 levels. All of the IAQ measurements for both buildings, however, fell under the DOSH-established standard limit
2	Nazli *et al.*, 2023	Manufacturing (food) Pulau Pinang $PM_{2.5}$, CO_2, TVOC, CO, T, RH SBSS-adopt from Department of Occupational and Environmental Medicine	Boosted regression tree (BRT)	Cooking techniques were found to be associated (p-value < 0.05) with the following symptoms: dry hands, scaling/itching scalp or ears, hoarse/dry throat, headache, eye issues, and nasal problems.
3	Zaki & Bari., 2022	Primary school in Pasir Gudang, Johor IAQ monitoring RH, AM, T, VOC, PM, HCHO	Descriptive statistic	Children who go to school in industrial and urban locations are susceptible to suffer injuries, especially when nearby human activity contributes to air pollution.
4	Azlan *et al.*, 2022	Educational building, Shah Alam T, RH, CO_2, PM_{10}, Biological contaminants, SBSS	Descriptive statistics, Chi square	Temperature and some symptoms, such as fatigue (p=0.036) and dizziness (p=0.031), are significantly correlated. Certain symptoms, including dry, irritated eyes (p = 0.047), headaches (p = 0.045), and fatigue (p = 0.040), were substantially correlated with relative humidity. Furthermore, a single symptom—itchiness, dryness, and irritation to the eyes—was substantially correlated with PM_{10} (p = 0.006).

	Author	Study Area	Data Analysis	Output
5	Othman *et al.*, 2022	Primary school in Kuala Lumpur IAQ monitoring $PM_{2.5}$	Descriptive Analysis	Average concentration of $PM_{2.5}$ was 42.0-23.1. Spatial analysis of $PM_{2.5}$
6	Ezani *et al.*, 2022	Outdoor (School., drop off and pickup zones) -Kuala Lumpur (suburban) $PM_{2.5}$, NO_2	ANOVA	Students that most effected towards $PM_{2.5}$ and NO_2 was the person that walking ad cycling. 10% exposure during school day comes from motorised travel to school and 5% comes from drop off and pick up zones
7	Ezani *et al.*, 2021	Indoor and Outdoor (university., UPM, Serdang)-suburban Apartment -indoor $PM_{2.5}$, traffic data	Mann Whitney Test	Reduction of motor vehicles during MCO caused decreasing emission of $PM_{2.5\ at}$ outdoor apartment. The distribution of $PM_{2.5}$ was higher during lunch time and gradually increased during preparation of the evening meal. It is noted that most cooking styles involved pan-frying and stir-frying for evening meal preparation, distinctive high peak between 17:30 to 18:30. During MCO the maximum concentration of $PM_{2.5}$ observed higher during evening at 52.2ug/m^3.
8.	Rasli *et al.*, 2021	Administrative offices, USM (Indoor) IAQ Monitoring CO, PM_{10}, O_3, TVOC, CO_2, RH, T, AM	Descriptive statistic	The T and RH were within the acceptable range of 23-26°C and 40-70%, respectively by ICOP, while the AM was very low and less than the acceptable threshold range of 0.15-0.5 m/s at 0.08 m/s, 0.04 m/s, and 0.02 m/s at Point 1, Point 2, and Point 3, respectively. The indoor air contaminants (CO, CH_2O, O_3, TVOC, PM_{10}, and TFC) met the standard level of ICOP, except for TBC and $CO_{2.}$ TBC exceeded the ICOP limit (500 cfu/m^3) at 1000 cfu/m^3 and 1500 cfu/m^3, at Point 1and Point 2, respectively, whereas CO_2 concentrations exceeded it (1000 ppm) at 1008.93 ppm at Point 2.

	Author	Study Area	Data Analysis	Output
9	Alwi *et al.*, 2021	Garment Manufacturing, Kota Bahru Kelantan (Indoor) IAQ monitoring and questionnaire.	Descriptive statistics	The prevalence of SBS among workers was 82.1%. The most common reported symptoms were feeling heavy headed, fatigue, and headaches with 85.0%, 83.3%, and 70.5% respectively. Other reported symptoms were nausea (25.5%), cough (64.7%), stuffy nose (58.4%), sore throat (58.2%), skin rash (54.4%), itchy scalp (35.8%), and eye irritation (19.7%). Only the mean temperature of 30.59 °C had exceeded the Malaysian Standard (ICOP-IAQ 2010) while both Relative Humidity (RH) and air velocity were below the Malaysian Standard with 54.85% and 0.31 m/s respectively. CO_2 was within the acceptable level with 651.25 ppm. $PM_{2.5}$ and PM_{10} were recorded 8 µg/m^3 and 80 µg/m^3 respectively.
10	Norback *et al.*, 2021	High school (Johor Bahru) Questionnaire, IAQ monitoring VOC, HCHO, CO_2, NO_2.	Descriptive and correlation	SBS symptoms such as headaches, rhinitis, fatigue and others symptoms caused by incompliances of physical and chemical parameters of insides the buildings itself.
11	Fu *et al.*, 2021	High school (Johor Bharu) Questionnaire Adopt questionnaire from Upsala University	ANOVA	SBS symptoms was completed by age (14-15): Student: 97.8%; males: 46.8%; females: 53.2% Female higher rates of tiredness ($p=0.01$) Headaches were more common in Malay and Chinese ($p=0.01$). SBS higher in female than male ($p=0.08$)
12	Yau *et al.*, 2023	Hospitals	Non-parametric analysis	The concentrations of elements accumulated in lichen U. misaminensis, as well as the photosynthetic parameters (an indicator of vitality) after the lichen samples were exposed to the outdoor and indoor environment in urban and rural areas for 2 months. The outdoor environment

	Author	Study Area	Data Analysis	Output
				showed higher concentrations compared to the indoor environment in both areas (urban and rural)
13	Sarkhosh *et al.*, 2021	Office in Kuala Lumpur	Regression	There was a strong significant relationship between the number of people in the room and the increased prevalence of SBS symptoms (p-value = 0.000). As 10.3% of the double rooms were positive SBS symptoms, this would increase to 23.1% in nine-person rooms.
14	Idris *et al.*, 2020	Kindergarten inside UKM IAQ monitoring $PM_{2.5}$, AM, T, RH	Principal Component Analysis	Average temperatures ranged from 28.81°C ± 31.62°C. The average relative humidity was 72.02% ± 0.58 for the upper floor and 71.19% ± 1.03 for the lower floor. The average mass concentration of $PM_{2.5}$ was 80.2 ± 31.1 mg/m^3 for the upper floor and 96.4 ± 27.0 mg/m^3 for the lower floor.
15	Khamis *et al.*, 2019	Office university, UTHM Questionnaire and IAQ Monitoring CO, CO_2, SO_2	Descriptive statistics	Previous study: T= 22.5ºC-24.7ºC Current study: T=24.9°C Previous study: AM=0.065m/s Current study: AM=0.19m/s Previous study: CO=13.5PPM Current study: CO=0.2PPM-12.2PPM Previous study: CO_2- 721.5PPM-478.5PPM Current study: CO_2-635ppm
16	Nejat *et al.*, 2019	UTM IAQ monitoring	Descriptive statistic	Air movement was ranged between 0.4 m/s to 0.5m/s. This study showed that IAQ analysis for airflow and air change rate was satisfy minimum requirements recommend by the standard. the high mean age of air was seen in speeds below the average (2.5 m/s) which led to a big dead zone area (area with air velocity below 0.1 m/s) in this range of the wind speed
17	Zainal *et al.*, 2019	Office workers in public university (indoor), UKM	Univariate, Multivariate and	Most reported symptoms were mucosal symptoms (19.6%), skin symptoms (10.2%), general symptoms

	Author	Study Area	Data Analysis	Output
		Questionnaire, IAQ monitoring	bivariate analysis	(18.7%) and this study showed 1.5 to 2 times higher findings compared to children in China study Men (22.1%) Smokers (175%) higher prevalence of being diagnosed with asthma than women up to 11.8%
18	Abdullah *et al.*, 2019	Kindergartens (Kuala Nerus Kuala Terengganu) IAQ monitoring PM, CO, CO_2 T, RH, AM	correlation	Ranged of the pollutants inside kindergartens was not normally distributed and Spearman correlation was used Exceed the limit for all parameters at certain time due to indoor activities
19	Alias *et al.*, 2021	Primary school (Kuala Lumpur) IAQ monitoring $PM_{2.5}$, HCHO, TVOC	descriptive statistics	Highest average for $PM_{2.5}$ concentrations in an indoor classroom was recorded at the school located in the industrial area (23.5 μg/m^3) followed by urban (18.6 μg/m^3) and suburban (9.58 μg/m^3). The indoor to outdoor (I/O) ratio values for $PM_{2.5}$ concentrations were slightly above one, indicating that open doors and windows highly affected indoor $PM_{2.5}$ concentrations
20	Dzullkiflli *et al.* 2018	Museum (Indoor and outdoor monitoring at Melaka Sultanate Palace Museum & History and Ethnography Museum) $PM_{2.5}$, SO_2, CO_2	Descriptive statistics	NO_2 exceed the standard in evening and outdoor contain high concentration compared to indoor. This is due to the location of the museum closed to roadside. SO_2 not exceed the limit. Exceed the limit almost all the time during operating hours for CO_2. $PM_{2.5}$ exceed the limit due to numerous sources of pollution such as motor vehicles, infrastructure, manufacturing, construction sites and more.
21	Hasrulnizzam *et al.*, 2018	Inside KTM Komuters ASHRAE Standard 62-2001	Regression analysis – to predict number of passengers	In the morning, a gradual increase in temperature was observed due to the rising number of passengers, highlighting the need for attention to air quality inside the cabin. In the evening, CO_2 levels inside the train

	Author	Study Area	Data Analysis	Output
				exceeded ASHRAE 62-2001 standards, showing a strong positive correlation between passenger numbers and CO2 levels.
22	Hazrin *et al.*, 2017	Educational PM, CO_2, T	Descriptive statistics	CO_2, produced by human respiration, does not impact classroom CO_2 levels during occupancy, likely due to the natural ventilation systems that bring in fresh air. Adequate ventilation is key to reducing CO_2 levels and maintaining a comfortable learning environment for students.

2.3 Sources of Indoor Air Quality

Main sources of indoor air pollution can be attributed to cooking and heating activities, namely the use of stoves, heaters, or fireplaces that burn gas, wood, or oil. These activities can result in the emission of dangerous gases such as CO and nitrogen dioxide (NO_2). Many household cleaners, air fresheners, and disinfectants include VOC, which are chemicals that can be harmful to indoor air quality. Building materials, particularly paints, varnishes, and specific types of furniture or flooring, can emit pollutants that contaminate indoor air. Tobacco Indoor smoking emits a multitude of noxious compounds into the air, impacting both smokers and bystanders. Mould and dust are typical contributors to indoor air pollution. Damp places can promote the formation of mould, while dust and pet dander accumulate over time. These pollutants can potentially aggravate allergies or respiratory problems. Pollutants originating from external sources, such as automobile emissions or industrial discharges, can infiltrate inside spaces through windows, doors, or ventilation systems (Taheri & Razban, 2021). The final item on the list was personal care products. Products such as hairspray, perfumes, and deodorants have the potential to emit hazardous substances that might negatively impact the interior air quality. By acknowledging these sources, we may implement measures to enhance indoor air quality and safeguard our well-being.

Table 2.4 presents the primary contributors to IAP, which include cooking and heating activities, cleaning chemicals, building materials, tobacco smoke, mould and dust, outdoor air, environmental factors, and personal care products. The simplified mechanisms of toxicity, as presented in Table 2.4, include the formation of harmful compounds, chemical irritation, the presence of particulate matter, and the release of allergens. Poor indoor air quality can have detrimental impacts on health, including respiratory problems, cardiovascular concerns, neurological effects, increased risk of cancer, and allergic reactions. Various indoor pollutants can lead to a range of health problems, including respiratory disorders and chronic diseases such as cancer or heart disease. Ensuring optimal air quality is essential for maintaining overall well-being.

Table 2.4 Sources of Indoor Air Pollution, Mechanisms of Toxicity, and Health Impacts on Indoor Air Quality (IAQ)

Pollutants	Source of emission/ Authors	Mechanism of toxicity	Health impacts
CO	Smoke from stoves, boilers, fuel-burning heaters, kerosene, and gas heaters. Burning fossil fuels such as oil, coal, natural gas and outdoor air pollution (Sarkhosh *et al*., 2021)	Formation of carboxy-hemoglobin and decreased oxygen supply higher bronchial function	Vomiting, nausea, weakness, dizziness, headache, and loss of consciousness Lung diseases and skin problems Headache, dizziness, weakness, nausea, vomiting, and unconsciousness begin to develop through the placenta and into the fatal circulation.
NO_2	Pollutants from motor vehicles in garages, fuel burning, Factory pollution, traffic (Zaki *et al*., 2022)	Significant elevation in bronchial activity and an increased risk of lung infection	Respiratory infections, wheezing, coughing, fever, chest pain, dyspnea, headache. Infections of the respiratory system that aggravate long-term respiratory conditions, including pneumonia, asthma, bronchial reactivity, and asthma
CO_2	Metabolism, combustion activities and motor vehicle usage Occupancy has a significant impact on IAQ (Hazri *et al*., 2017)	Blocking acetylcholinesterase from hydrolyzing	Fatigue and headaches, Higher concentration leads to nausea, vomiting, and dizziness. Respiratory infection, lung conditions, heart arrhythmias, convulsions, cerebral illness and trauma victims, and decreased performance
VOCs	Pesticides, adhesives, varnishes, stains, polishes, cleansers, lubricants, sealants, dyes, copy machines, printers, tobacco products, perfumes, dry-cleaned clothing, building materials and furnishings, etc. (Ghia *et al*., 2022)	Carcinogenic, mutagenic, neurotoxic, and genotoxic	Irritation in eyes, throat, skin, and nose. Headaches, respiratory symptoms, fatigue, damage to the kidney, central nervous system and liver, trigger symptoms of allergy. Breathing difficulties, dry throat, impatience. Disorders such as asthma, anaphylaxis, cardiovascular, and cancer

Pollutants	Source of emission/ Authors	Mechanism of toxicity	Health impacts
Respirable particulate	Environmental factors such as cooking, combustion activities, outside environment, and cleaning activities (Khamis et al., 2019). the office equipment, such as printers, fax machines, photocopiers, and central air conditioning systems (Awang *et al.*, 2023) Antigen from the flower (Zaki *et al.*, 2022)	Oxygen stress and inflammation on a systemic level	Premature death by heart or lung disease, irregular heartbeat, Trigger symptoms of allergy Attacks of asthma, long-term bronchitis, heart disease, lung cancer, diabetes, respiratory disorders, limited activity, and early death
Humidity	Ventilation system (Alias et al., 2021; Hazrin et al., 2017)	Germs and viruses cause disease to thrive and grow in the air with a relative humidity of more than 60% and can cause respiratory problems (respiratory droplet dispersal via droplet and airborne means. The size of the droplets affects how quickly they settle (droplet/fomite spread) or how long they stay in the air (airborne spread).	Eyes become dry and irritated, skin gets flaky, dries out the mucous membrane lining the respiratory tract and increases heat disease admissions.
Temperature	Ventilation system (Soleimani et al., 2019)		Sweating, tired eyes, light-headedness, rapid breathing, elevated heart rate, and discomfort that is warm

Source Apportionment in IAQ monitoring

PCA is a powerful statistical technique often used in the analysis of IAQ data. It helps to simplify and interpret complex datasets by reducing dimensionality while preserving as much variability as possible (Greenacre *et al.*, 2022). PCA is a method that transforms a large set of variables into a smaller set of uncorrelated variables called principal components (Kherif & Latypova, 2020). These components capture the most significant variations in the data (Schreiber, 2021). Application of PCA in indoor air quality analysis as one of the data reduction methods (Hasan *et al.*, 2021). The purpose of data reduction in indoor air quality studies often involves multiple variables (e.g., levels of various pollutants, temperature, humidity). PCA reduces the number of variables by combining correlated variables into principal components, which can simplify the dataset, making it easier to analyse and visualize (Zhao *et al.*, 2020).

Identifying key pollution was one of PCA's strengths. PCA's capability helps to identify which pollutants contribute most significantly to the variation in air quality (Cotta *et al.*, 2020). This helps analysis to focus on the most critical factors affecting IAQ, aiding in targeted interventions (Rodríguez-Urrego & Rodríguez-Urrego, 2020). PCA can reveal patterns and correlations between different pollutants, potentially indicating common sources of indoor pollution, which can help in tracing the origin of pollution, such as identifying if certain activities or materials contribute to specific pollutant clusters (Liu *et al.*, 2021). PCA results are often visualized in plots or graphs, such as biplots or scree plots, which show the relationships between principal components and original variables (Wen *et al.*, 2019). This output helps provide a clear and intuitive way to understand complex data and highlight major trends. The last point was analysing the principal components; researchers can interpret the underlying structure of the data and identify the most influential factors affecting IAQ. This structure can enhance understanding of how different variables interact and impact air quality.

2.4 Previous studies about spatial mapping

Indoor air quality spatial mapping entails generating a comprehensive depiction of the variations in air quality across indoor air. This can aid in the identification of regions with poor air quality, optimizing ventilation systems, and enhancing the general health of indoor environments. There are several prevalent strategies employed in geostatistical methods, machine learning, and simulation models. Geostatistical methods employ spatial interpolation techniques, such as kriging, to estimate air quality levels in areas located between sensors. This allows the generation of a continuous representation of air quality throughout the area. Figure 2 showed the screening process to determine the best method used for simulating RSP inside the building.

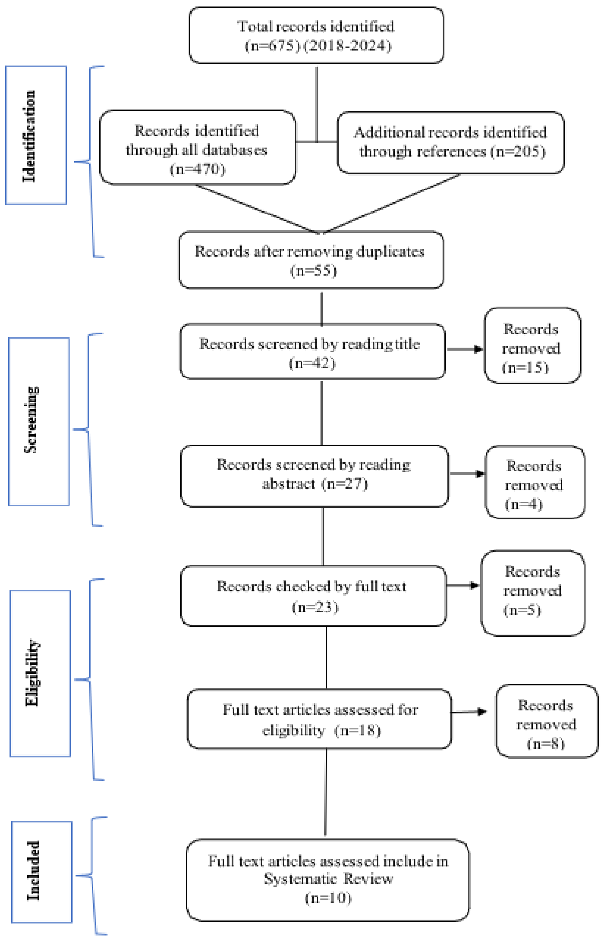


Figure 2.2 Stages of spatial mapping determination using CFD

CFD was not initially designed for the purpose of modelling buildings. Nevertheless, during its evolution, this technique can be utilized in diverse domains, including heat transfer, fire simulation, the design of different turbo engines, the study of air pollutant flow phenomena, and the analysis of thermal comfort. Utilizing machine learning algorithms to assess sensor data and forecast air quality trends or detect pollution sources by examining spatial and temporal patterns. Simulation models include sophisticated techniques such as Suffer and CFD models to replicate airflow and the spread of pollutants. These models take into account the building's layout and ventilation systems. This tool can forecast air quality in various situations and assist in the development of more effective ventilation schemes. CFD has been utilized since the 1970s to calculate airflow in indoor and constructed spaces, regardless of whether it is caused by wind, buoyancy, or mechanical ventilation systems like HVAC and fans. Once a CFD model is built, different types of studies can be performed. For example, various studies have analyzed the indoor flow pattern, the influence of sub-models representing heat and mass sources from animals and litter, and the impact of different boundary conditions on the internal field velocity. A few papers refer to the application of CFD models in studying naturally single-sided ventilation, cross-mechanical ventilation, tunnel ventilation, and mechanical single-sided ventilation for poultry houses. However, it is noted that the CFD technique has not been widely applied to study the tunnel ventilation system used in poultry houses. Therefore, the overall aim of the present study is to make contributions to the evaluation of indoor environmental parameters for giving enough ventilation. The objectives of this work are to develop a three-dimensional CFD model with different boundary conditions to simulate the indoor airflow, air temperature, and relative humidity distribution. Validate the CFD model by comparing simulated results with the field measurements from an experimental-oriented tunnel-ventilated laying hen house. Provide scientific data to evaluate the ventilation system's performance and guidance on optimizing the ventilation design using the validated CFD model.

Currently, the application of CFD has extended beyond the study of air's physical phenomena to include the assessment of thermal comfort and IAQ. CFD is a computer-based simulation method that uses mathematical equations to solve and visualize physical phenomena numerically. Equations discretize the collection of variables to represent the original physical occurrences in space and time. It determines the precise spatial arrangement of airspeed, temperature, and levels of contaminants by solving the Navier-Stokes and species-conservation equations. CFD can be categorized into three main methods: direct numerical simulation (DNS), large eddy simulation (LES), and the Reynolds averaged Navier-Stokes equations with turbulence models (RANS). The DNS method is highly reliable for simulating contamination dispersion, but it requires significant computer resources and can take many years to predict, even in a small facility. LES outperforms DNS with excellent outcomes. However, it remains impractical because of its requirement for substantial computer memory and extended computational time spanning several weeks. The RANS equation, which employs a turbulence model, is the most commonly utilized method for simplifying the calculation of turbulence effects. Although there is a minor inaccuracy, the result is still excellent in providing precise information on the distribution of airflow and contaminant concentration. Furthermore, it significantly reduces the requirements for computer memory and computing time.

To obtain reliable outcomes, users must possess knowledge of several complex techniques. The key components of the study include the geometric properties of the item being examined, the process of dividing the volume into discrete elements (meshing), the model used to simulate turbulence, and the conditions at the boundaries of the system. Data processing is essential for analyzing and presenting convergent simulation results. The validity of the results is substantially influenced by the accuracy and precision of the applied boundary conditions, meshing density, resolution method, and assumptions used. Ansys Fluent, Phoenics, and Airpak are all commercial CFD software. Table 2.4 provides a summary indicating that air quality research commonly utilizes three distinct types of software to simulate air movement and indoor pollutants. The available models are CONTAM (a multi-zone model), Ansys Fluent (a CFD model), and CONTAM - CFD0 (a combination of multi-zone and CFD models). This table summarizes a variety of studies utilizing different computer simulation models and software to assess indoor air quality (IAQ) in various environments. The primary software used in these studies includes CFD (Computational Fluid Dynamics) models combined with CONTAM (multizone airflow model) and Ansys Fluent, which are employed to simulate airflow, pollutant dispersion, temperature, humidity, and other

IAQ variables. The studies span diverse building types, including housing, office spaces, poultry houses, laboratories, and hospitals, showcasing the flexibility of simulation models across different environments.

Simulation software showed most studies use CFD models, with some combining CFD with CONTAM for more detailed analyses of air movement and pollutant transport. The Ansys Fluent software is particularly common in studies involving complex airflow and pollutant dispersion. A range of IAQ parameters are simulated, including ventilation rates, pollutant concentration, temperature, air movement, and moisture. These simulations are used to optimize ventilation systems, understand airflow dynamics, and predict pollutant behaviour in various settings. The studies emphasize improving IAQ through better building design, such as optimal window placements, air curtain use, and proper ventilation types. They also address specific concerns, such as pollutant transport in medical or laboratory settings, and the impact of weather conditions (wind direction and velocity) in outdoor urban environments. Some studies highlighted the importance of using transient ventilation rates (e.g., in Murga *et al.*, 2019) and sensitivity analysis (e.g., Cheng *et al.*, 2021) to assess how changing conditions affect IAQ. Additionally, studies like those of Heibati et al. and Wang et al. discuss the trade-offs between different turbulence models and computational costs for more accurate results. Overall, the combination of CFD models and CONTAM software provides an effective means to simulate IAQ and optimize building ventilation, though the limitations of these models in fully capturing chemical reactions and pollutant transformations are also noted.

Multi-zone model (CONTAM)

The CONTAM software allows for multi-zone modelling, which accurately simulates air mass and pollutant concentrations in structures that include internal partitions, such as office buildings, hospitals, or high-rise apartment houses with many rooms (Yan *et al.*, 2022; Mei & Gong, 2019). This simulation tool also enables the modelling of entire buildings, including multiple ventilation zones, with high computational efficiency (Dols *et al.*, 2021). In addition, it has the capability to consider the existence of mobile occupants as a factor in the simulation (Wang *et al.*, 2022). Furthermore, CONTAM can be integrated with energy analysis software such as EnergyPlus and TRNSYS (Tian *et al.*, 2020). An obstacle to using this program is the challenge of effectively employing it due to the significant amount of input needed. Input is required for each zone regarding parameters pertaining to all internal partitions of the building (Fine & Touchie, 2021). Furthermore, both the COMIS and CONTAM systems lack a user-friendly interface for data input, and their graphical presentation of findings is similarly unappealing. Another notable constraint is that this model can assess the overall performance of the building, but it cannot predict the exact distribution of temperature and air velocity within the room (Tian *et al.*, 2020). This limitation arises from the assumption that the pressure, temperature, and pollutant concentration in each zone will be uniform (Less *et al.*, 2019). Air is regarded as fixed in order to prevent any influence on the air pressure results caused by air movement in the area (Ferdyn-Grygierek *et al.*, 2019; Dols *et al.*, 2015). Therefore, it is not ideal for accurately depicting genuine natural ventilation, which involves varying temperature, velocity, and air pressure (unsteady) (Sarna *et al.*, 2022; Dols *et al.*, 2021; Kolarik *et al.*, 2019). Furthermore, it is essential to supplement the implementation of this model with additional models for evaluating thermal comfort (Wang *et al.*, 2020). Modelling complex structures or expansive areas can be particularly challenging. Although it has imperfections, the scientific community has embraced the results of simulations utilizing this multi-zone model to analyse airflow and the spread of pollutants.

Ansys Fluent Software

Ansys Fluent is now the leading brand of CFD software (Bhatti *et al*, 2022). Proficiency in numerical fluid dynamics and the use of high-performance computers are necessary. The CFD simulation outcomes must be validated by comparing them with experimental results. The primary benefit of the CFD model lies in its user-friendly and visually captivating interface and graphics (Dang *et al.*, 2022). Ansys Fluent's latest iteration incorporates a 3D software called Design Modeler, which facilitates the input of data and the creation of geometric structures (Gialelis *et al.*, 2023). Unlike CONTAM, Ansys Fluent uses fluid mechanics to accurately compute the dynamics of air, mass, heat, and contaminants (Kochkov *et al.*, 2021; Mohammadi & Calautit, 2021). It excels in providing intricate and detailed simulations of natural and mechanical ventilation (HVAC) under both steady-state and unsteady-state conditions (Wang *et al.*, 2020; Chen *et al.*, 2020). Nevertheless, the simulation now requires additional time. Despite the requirement for specialized expertise and effort, CFD remains the most informative simulation program currently accessible.

CONTAM – CFD0 Software (Multi-zone and CFD model combination)

An intermediate solution for combining the multi-zone model and CFD can be achieved by using the widely used applications CONTAM and CFD0. In CONTAM models, mistakes commonly arise in the atria, which are areas with significant natural ventilation apertures, as well as in zones where contaminants are sourced (Waeytens *et al.*, 2019). CFD0 addresses the shortcomings in these areas by simulating fluid movement using the Reynolds-averaged Navier-Stokes (RANS) equation. The multi-zone model calculates the average airflow characteristics and pollutants, while the CFD technique predicts the three-dimensional dispersion of these parameters (Cheng *et al.*, 2021). The integration of CFD0 and CONTAM allows for the inclusion of data pertaining to wind pressure and exterior contaminant concentrations in the CONTAM room simulation. Additionally, it enables the utilization of comprehensive CFD zone descriptions in the simulation of airflow and contaminant distribution in CONTAM (Du *et al.*, 2019). Furthermore, this combination significantly improves CONTAM's effectiveness in accurately predicting airflow and temperature distribution while also increasing the speed of CFD computation (Barbosa *et al.*, 2018). Nevertheless, adjustments are evidently necessary for the input and output data due to the utilization of two distinct programs. Iterations are necessary to determine the most efficient method of converting data and transmitting information between the two programs (Heibati *et al.*, 2021; Murga *et al.*, 2019).

Table 2.5 IAQ studies with various computer simulation models and software used

Author	Object (location)	Simulation model: software	Variable	Measurement conditions	Highlight of Method
Heibati *et al.*, 2021	Housing	CFD CONTAM	Relative humidity, temperature	Airtight-fan off, airtight-fan on, leaky-fan off, and leaky-fan on	CONTAM is focused on heat and moisture transport. The pollutant transport modeling in CONTAM is too simplified for specific indoor air quality studies. It might not fully capture chemical reactions, deposition, or transformation of pollutants within the indoor environment.
Murga *et al.*, 2019	Office	Combination CFD- multizone model: CFD-0 CONTAM	Wind direction and wind velocity	ventilation rate and air change per hour (ACH)	Combining CFD with control volume analysis, the transient ventilation rate, which accounts for fluctuations in wind pressure throughout the day, can be calculated.
Gialelis *et al.*, 2023	Office	CFD- Ansys	Breathing rate, wind speed	Breathing flow for occupants inside the building	Observations have been made regarding the poor quality of indoor environments under different airflow conditions and at specific times of the day
Du *et al.*, 2019	Poultry house	CFD-CONTAM multizone	Air movement, temperature, wall temperature, air moisture	Inlet and outlet flow	The verified CFD model generated illustrative planes, which were then utilized to examine the potential optimal air intake configurations for tunnel-ventilated poultry houses.
Waeytens *et al.*, 2019	Laboratory	CFD- CONTAM multizone model	Boundary condition	The best location to put the sensor inside the building	The numerical method is utilized to analyse a physical laboratory space with regulated airflow conditions. An initial experimental campaign has been carried out to verify the proposed numerical technique.

Author	Object (location)	Simulation model: software	Variable	Measurement conditions	Highlight of Method
Barbosa *et al.*, 2018	Hospital	Combination CFD- multizone model: CFD-0 CONTAM	Boundary condition	Airborne contaminant transport	The CFD-0 model yields accurate outcomes when used to simulate the dispersion of pollutants in laboratory and hospital environments.
Wang *et al.*, 2020	Housing	CFD-Ansys Fluent	Window type, Pollutant source location, wind velocity, wind direction	ACH, pollutant concentration	LES offers more accuracy for time-dependent, complex turbulence but at a much higher computational cost. RANS provides faster results with lower computational requirements and is suitable for many industrial applications where steady-state accuracy is acceptable.
Chen *et al.*, 2020	Kitchen-Housing	CFD: Ansys Fluent 19.04	Air curtain, volume exhaust	Concentration distribution, air age	The enhanced computational fluid dynamics (CFD) model is a pragmatic and dependable instrument for assessing indoor air quality (IAQ) and thermal comfort in the kitchen.
Mohammadi & Calautit, 2021	Urban canyon-city	CFD: Ansys Fluent	Ventilation type, window opening behavior, location and geometry of urban canyon, wind direction	Pollutant concentration	Among the k-ω BSL, k-ε RNG, and RSM turbulence models, k-ω is the most reliable model.
Cheng et al, 2021	Office with many partitions	CFD: Ansys Fluent	Door size, the material of the door, solar radiation	Concentration and distribution of PM	Sensitivity analysis can facilitate the simulation of multi-zone CFDs without the requirement for excessively complex or detailed meshing.

In conclusion, the choice of tool for IAQ studies depends on the complexity of the environment, as shown in Table 2.6, the level of detail required, and the available computational resources. ANSYS Fluent is the best option for high-fidelity, room-level IAQ simulations. It excels in detailed airflow and pollutant transport analysis within complex environments, making it ideal for critical settings where tight control over air exchange and pollutant levels is essential (Cheng *et al.*, 2021). However, it is resource-intensive and requires expertise. CONTAM is optimal for multi-room or whole-building IAQ studies, where airflow between zones is key. It simplifies multi-zone analysis, providing building-wide insights into ventilation practices without the need for complex CFD modelling (Barbosa *et al.*, 2018). It's ideal for large-scale studies but lacks the detailed flow analysis capabilities of Fluent. CFD0 is a simple and lightweight tool suitable for smaller, less complex environments (Waeytens *et al.*, 2019). It provides basic IAQ insights but lacks the depth and versatility for detailed analysis or advanced simulations. Therefore, it's a good choice for scenarios with limited computational resources. Thus, selecting the appropriate tool depends on the specific goals of your IAQ study, whether detailed room-level analysis or large-scale building-wide airflow modelling is needed.

Table 2.6 Comparison of ANSYS Fluent, CFD0, and CONTAM for Indoor Air Quality (IAQ) Simulations

Feature	**ANSYS Fluent**	**CFD-0**	**CONTAM**
Computational Requirements	High (computationally heavy)	Low (lightweight)	Low (multi-zone models)
Ease of Use	Complex (steep learning curve)	Simple (easier to use)	Simple (IAQ-focused)
IAQ Focus	General-purpose CFD tool	IAQ and indoor airflow focused	IAQ and multi-zone focused
Post-Processing Capabilities	Advanced visualization tools	Basic visualization tools	Basic reporting, no CFD-level visualization
Use Case	Detailed single-room studies, complex airflow, pollutants.	Small-scale IAQ, simple geometries	Whole-building ventilation, zone-to-zone airflow

2.5 Indoor Air Quality evaluation from previous study

Previous studies, as shown in Table 2.6, showcase the wide array of modelling tools employed to examine IAQ. Time series models, such as the one employed by Wei *et al.* (2022), are highly suitable for continuous monitoring and detecting thresholds of pollutant concentrations. On the other hand, multiple linear regression, as demonstrated in the study by Yuchi *et al.* (2019), is particularly effective in establishing connections between different environmental factors and levels of air pollutants. Generalized linear models and multiple logistic regressions, employed by Ravindra *et al.* (2019) and Alwi *et al.* (2021), offer a comprehensive insight into the relationship between IAQ and health outcomes, as well as symptoms such as SBS symptoms and selection of the paper shown in Figure 2.3.

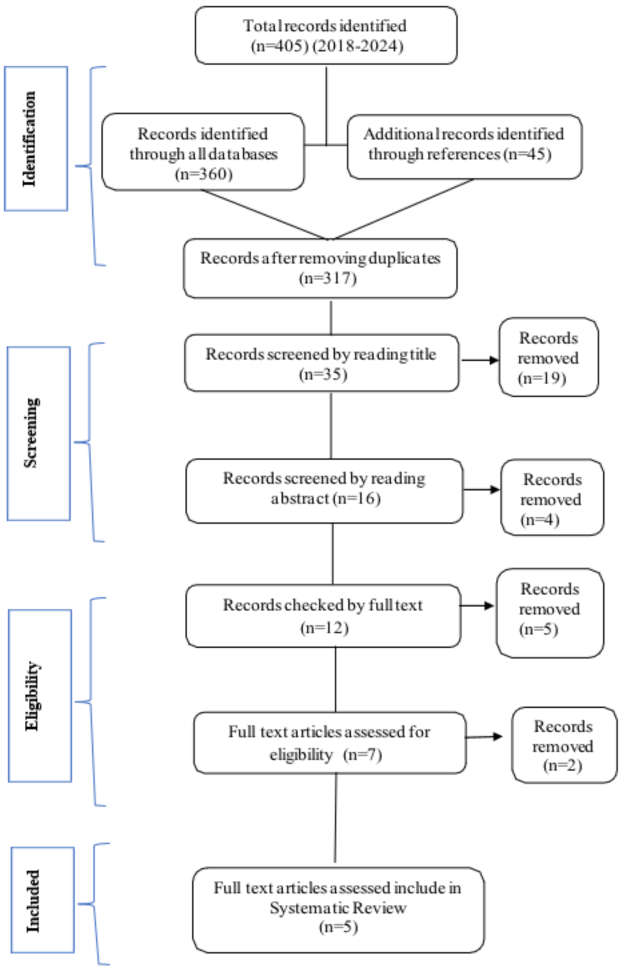


Figure 2.3 Stages determination of the best IAQ model for prediction qualitative and quantitative data

When comparing Gamma distribution GLM with other models like Multiple Linear Regression (MLR), Time Series Analysis, Logistic Regression, and Multiple Logistic Regression, it's essential to consider how each method handles different types of data and research objectives. There are advantages and disadvantages of each model depending on the types of data and its application as summarized in Table 2.7. Gamma Distribution GLM advantages are that it can handle skewed continuous data, incorporate both continuous and categorical predictors, and also have flexibility (Islam *et al.*, 2021; Vieira *et al.*, 2019). The gamma distribution is excellent for modelling positive and skewed continuous variables, such as pollutant concentrations and air exchange rates (Fu *et al.*, 2022). It can also effectively model right-skewed data (Huang *et al.*, 2020). Allows integration of categorical predictors (e.g., presence of SBS symptoms) and continuous predictors (e.g., temperature, humidity) in the same model besides providing flexibility with different link functions (e.g., log link) and can capture complex relationships between predictors and outcomes (Orabi, 2020; Ravindra *et al.*, 2019). Disadvantages of Gamma distribution GLM was complexity which requires careful specification of the distribution and link function. Incorrect model assumptions can lead to biased results (Sarkhos *et al.*, 2021). Assumption dependence was one of the disadvantages of the GLM distribution model, which assumes that the dependent variable follows a Gamma distribution, which may not always be appropriate for all continuous data (Belotti *et al.*, 2020).

The second model was MLR. This model's strength was its simplicity and interpretability, which made it easy to implement and interpret. It models linear relationships between continuous variables and predictors. MLR can handle continuous predictors and determine model relationships between continuous predictors and outcomes (Alwi *et al.*, 2021). The model's weakness was its assumption of normality, which assumes that residuals are normally distributed. This can be problematic for skewed IAQ data, leading to inaccurate results if the data are not normally distributed (Yuchi *et al.*, 2019). Besides that, the deficiency of the model is limited to categorical data. Categorical variables can be included via dummy coding, but MLR is less effective at capturing complex interactions between categorical and continuous variables.

The next model was time series analysis, which consists of temporal dynamics, which are ideal for analysing data collected over time, capturing trends, seasonality, and temporal dependencies, and suitable for forecasting (Ali *et al.*, 2022). Useful for predicting future values based on historical data, which is valuable for understanding how pollutant levels change over time (Wei *et al.*, 2022). The weakness of the model is that it was not designed for categorical data (Elshawi *et al.*, 2019). It primarily focuses on continuous data over time and does not directly handle categorical predictors like SBS symptoms. Last was time series models can be complex and require careful parameter tuning (Truquet, 2019). Integrating categorical data requires additional steps and can be less straightforward (Nelias, 2021).

Logistic Regression has a few advantages which well-suited for modelling binary or ordinal outcomes. Besides can also provide odds ratios that are easy to interpret in terms of the likelihood of an outcome occurring based on predictors (Kim *et al.*, 2019). The disadvantages of logistic regression are that it is not suitable for continuous outcomes, and it cannot model continuous variables like pollutant concentrations directly (Arulmozhi *et al.*, 2021). It focuses on categorical or binary outcomes. Disadvantages of logistic regression also have less effectiveness at capturing complex interactions between predictors and continuous outcomes compared to GLMs with a Gamma distribution (Laurent *et al.*, 2021).

Multiple Logistic Regression was one of the models compared in this chapter. It has advantages, such as its capability to handle multiple categorical outcomes (Afrabandpey *et al.*, 2019). This model is suitable for modelling multiple categorical or ordinal outcomes, which can be useful if SBSS is measured with more than two categories or levels (Loy-Benitez *et al.*, 2019). Flexibility with predictors was one of the multiple predictors to assess their impact on the outcome (Park *et al.*, 2023). Disadvantages were not for continuous outcomes, which, like logistic regression, is not designed for continuous outcome variables such as pollutant concentrations (Tripathi., 2023; Elshawi *et al.*, 2019). Complexity is one of the disadvantages of multiple logistic regression can become complex with many predictors and interactions, potentially leading to model overfitting (Yuchi *et al.*, 2019). Each of these models provides vital insights into the field of IAQ research, enhancing our understanding of how to sustain healthy indoor environments through sophisticated predictive models, data analysis, and real-time control systems.

Table 2.7 Summary IAQ models categorized by data type and output

Authors	**Type of model**	**Types of data**	**Observation**
Wei *et al.*, 2022	Time series	Scale (Quantitative) Variables: CO_2	Determines the ideal threshold by assessing the reconstruction loss rates for each data point across all time-series sequences.
Yuchi *et al.*, 2019	Multiple Linear Regression (MLR)	Scale (Quantitative) Variable: $PM_{2.5}$, Temp, RH, RH, SO_2, NO_2. CO_2	Create predictive algorithms for estimating weekly indoor $PM_{2.5}$ concentrations and evaluate and contrast the effectiveness of Multiple Linear Regression (MLR) and Random Forest Regression (RFR).
Kim *et al.*, 2019	Logistic regression	Ordinal, Nominal (Qualitative) Variables occupant ventilation behaviour; development of the automatic ventilation control	The automatic ventilation control algorithm is integrated into a building ventilation system that is linked to different IEQ measurements,
Ravindra *et al.*, 2019	Generalized Linear Model (GLM-GAM)	Nominal (Qualitative) Scale (Quantitative) Variables Ambient air pollutants, climate change, and health	A generalization of ordinary linear regression, which allows response variables to have errors that are not normally distributed and determines the relationship between the variables
Alwi *et al.*, 2021	Multiple Logistic Regression (Chi-Square)	Ordinal, Nominal (Qualitative) Scale (Quantitative) Variables IAQ parameters &SBSS	Association between IAQ level and SBS symptoms

When analysing a dataset with both continuous and categorical variables, particularly if the continuous data is skewed, the Gamma Distribution GLM offers several advantages that make it a frequently suitable choice. Here’s an expanded view of why the Gamma Distribution GLM is often preferred in such scenarios, such as the capability of the Gamma Model to handle skewed continuous data and categorical data. Continuous variables such as indoor air pollutant concentrations (e.g., $PM_{2.5}$, CO, CO_2, TVOC, and HCHO) often exhibit skewed distributions, meaning they are not symmetrically distributed around the mean. The Gamma distribution is specifically designed to handle positive, continuous data that are right-skewed or have long tails (Ahlmann-Eltze & Huber, 2021). The Gamma Distribution GLM can accommodate the non-normality of skewed data by using a Gamma distribution with a suitable link function (e.g., the log link) which allows for accurate modelling of data that does not conform to the assumptions of normality required by traditional linear models (Perley & Coleman, 2024).

The incorporation of both continuous and categorical predictors is one of the strengths of the gamma distribution model. Continuous predictors can be included in the gamma distribution. The model can include continuous variables such as temperature, humidity, and various pollutant levels as predictors. This helps in understanding how these continuous factors influence the outcome variable, whether it be another continuous variable or a transformation of the outcome. Gamma Distribution GLM can also incorporate categorical variables (e.g., SBS symptoms) through dummy coding or factor variables. This allows the model to assess the impact of different categorical levels on the continuous outcome, facilitating a comprehensive analysis of how various factors contribute to indoor air quality.

Flexibility in model specification, which selection of link functions. GLMs offer flexibility through different link functions (e.g., log, identity) that relate the mean of the response variable to the predictors. For Gamma Distribution GLMs, the log link function is commonly used, which is effective for modelling the multiplicative effects of predictors on the outcome (Mentese *et al.*, 2020). The Gamma distribution allows for modelling the variance of the response variable as a function of its mean, which can be crucial when dealing with data that exhibits heteroscedasticity (i.e., non-constant variance) (Belotti *et al.*, 2020). Gamma Distribution GLMs provide accurate parameter estimates and robust standard errors for the predictors, which helps in making reliable inferences about the relationships between predictors and the outcome variable (Soleimani *et al.*, 2019). In addition, the gamma model facilitates diagnostics to assess the goodness of fit and to identify any potential issues, such as outliers or leverage points. This ensures that the model's assumptions are met and that the results are credible.

The gamma distribution in GLMs is particularly suited for modelling positive, continuous data with skewness, such as pollutant concentrations or symptom severity scores, for the following reasons due to the capability to handles positive data. IAQ measurements like pollutant concentrations (e.g., VOCs, $PM_{2.5}$, HCHO, CO, CO_2, PM_{10}) or symptom scores are inherently positive, making gamma an appropriate choice. Gamma distribution effectively captures the right-skewed nature of many IAQ-related variables, where extreme values (e.g., high pollutant spikes) are rare but significant. By using the log-link function, the GLM-Gamma model transforms the dependent variable into a linear relationship with predictors, improving model interpretability and accuracy (Perley and Coleman, 2024). This approach avoids the pitfalls of ordinary least squares regression, which assumes normally distributed errors. Integration of qualitative and quantitative data using GLMs allow for both categorical predictors (e.g., room type, HVAC presence, symptoms) and continuous predictors (e.g., pollutant concentrations, humidity levels). Interaction terms can capture relationships between qualitative and quantitative IAQ factors, enhancing predictive capability (Vieira *et al*., 2019). The gamma model accommodates heteroscedasticity (non-constant variance in residuals), which is common in IAQ data. Model's non-normal data and handles both continuous and categorical variables which can be handle by GLM-Gamma distribution models which relevance to IAQ datasets which captures the characteristics of IAQ measurements and symptom severity effectively (Licina & Yildrim, 2021). These can facilitates understanding of how specific IAQ factors impact outcomes. These models can provide accurate predictions for planning interventions and mitigating SBS symptoms. In conclusion, the GLM-Gamma model is a robust choice for addressing the complexities of IAQ prediction by integrating diverse data types and addressing key statistical challenges.

2.6 Summary of the chapter

Research conducted from 2017 to 2023 in Malaysia highlights a significant relationship between IAQ and SBS symptoms across various indoor environments, such as offices, schools, residential buildings, and manufacturing facilities. Poor IAQ has been consistently linked to the prevalence of SBS symptoms, including headaches, fatigue, dry or irritated eyes, dizziness, nasal problems, and respiratory discomfort. The main contributors to poor IAQ include high levels of particulate matter (PM_{10} and $PM_{2.5}$), volatile organic compounds (VOCs), carbon dioxide (CO_2), and inadequate temperature and humidity control.

PCA has proven to be an essential analytical tool for identifying pollutant sources, quantifying their impacts, and guiding effective IAQ management strategies. Enhanced regulations, coupled with proactive building design and maintenance, are crucial to reducing SBS prevalence and improving indoor environments.

In Ansys Fluent, more efficient algorithms or simplified models that can reduce computational requirements without sacrificing accuracy are needed. Research could explore ways to optimize the simulation process for indoor environments to make it more accessible for real-time applications or large-scale studies using Ansys Fluent. More validation studies, including experiments in controlled environments, can enhance confidence in ANSYS Fluent models for IAQ applications compared to other models, in which ANSYS Fluent more represents the real-time situation. This can be especially valuable in complex geometries such as hospitals, laboratories, and multi-occupant spaces. Implementing uncertainty quantification techniques can improve the robustness of CFD simulations by providing a range of possible outcomes, which can be valuable for decision-making in real-world building operations.

When dealing with a dataset that contains both continuous and categorical variables, especially if the continuous data is skewed, the Gamma Distribution GLM is frequently the most suitable option. This is because the Gamma Distribution GLM is capable of handling skewed distributions and can effectively incorporate both types of predictors. MLR, or multiple linear regression, is a less powerful method when dealing with data that is skewed or when there are categorical predictors. Time Series Analysis is a useful tool for examining patterns across time, but it is not suitable for studying categorical data. Logistic Regression and Multiple Logistic Regression are optimal for modelling categorical outcomes, but they are not appropriate for continuous variables such as pollutant concentrations. The choice of an appropriate model is contingent upon the research inquiry, attributes of the data, and objectives of the study.

CHAPTER 3

METHODOLOGY

3.1 Introduction

This chapter explains the overall research conducted to achieve all objectives in this study. The overview of the research flowchart is shown in Figure 3.1. It started with site selection and information on the study area. Site selection is essential to determine significant site selection for this study. Four buildings with different economic activities represent the dominant sub-economy in Terengganu. The parameters measured in this study consists of IAP which consists of physical parameters (air movement, AM (m/s); temperature, T (^{o}C); relative humidity, RH (%)), chemical parameters (carbon dioxide, CO (ppm); total volatile organic compound, TVOC (ppm); formaldehyde, HCHO (ppm); respirable suspended particulates, RSP also known as particulate matter PM (mg/m^3)) and ventilation performances indicators (carbon dioxide, CO_2 (ppm)). Sampling or IAQ monitoring was conducted during the monsoonal season because Terengganu was one of the states significantly affected during the monsoonal season, consisting of Southwest Monsoon (SWM) and Northeast Monsoon (NEM). The selection of instruments used to measure IAP was in the data acquisition and pre-processing section, which also consists of pilot tests or pre-processing for IAQ monitoring and questionnaires. Questionnaires were distributed to occupants or workers to determine the presence of past and present symptoms of SBS Symptoms. Flow charts proceed with data analysis, which consists of four phases; each phase was conducted to embark on each objective in this study. Phase 1 showed the data analysis conducted trends for ventilation performance indicators, air pollutants, and physical and chemical parameters. Data analysis proceeds with spatial mapping using CFD simulation using Ansys Fluent to determine the air movement inside the building at study areas. Phase 3 in data analysis investigated influencing factors inside the building using one type of factor analysis, PCA, to determine the primary source that contributes towards air pollutants inside the study areas. Phase 4 establishes the statistical model for the prediction of SBS symptoms and IAP concentration using the GLM, and this study used gamma distribution because the datasets show that gamma distribution is suitable for these types of datasets. After developing the model, the equation produced was validated.

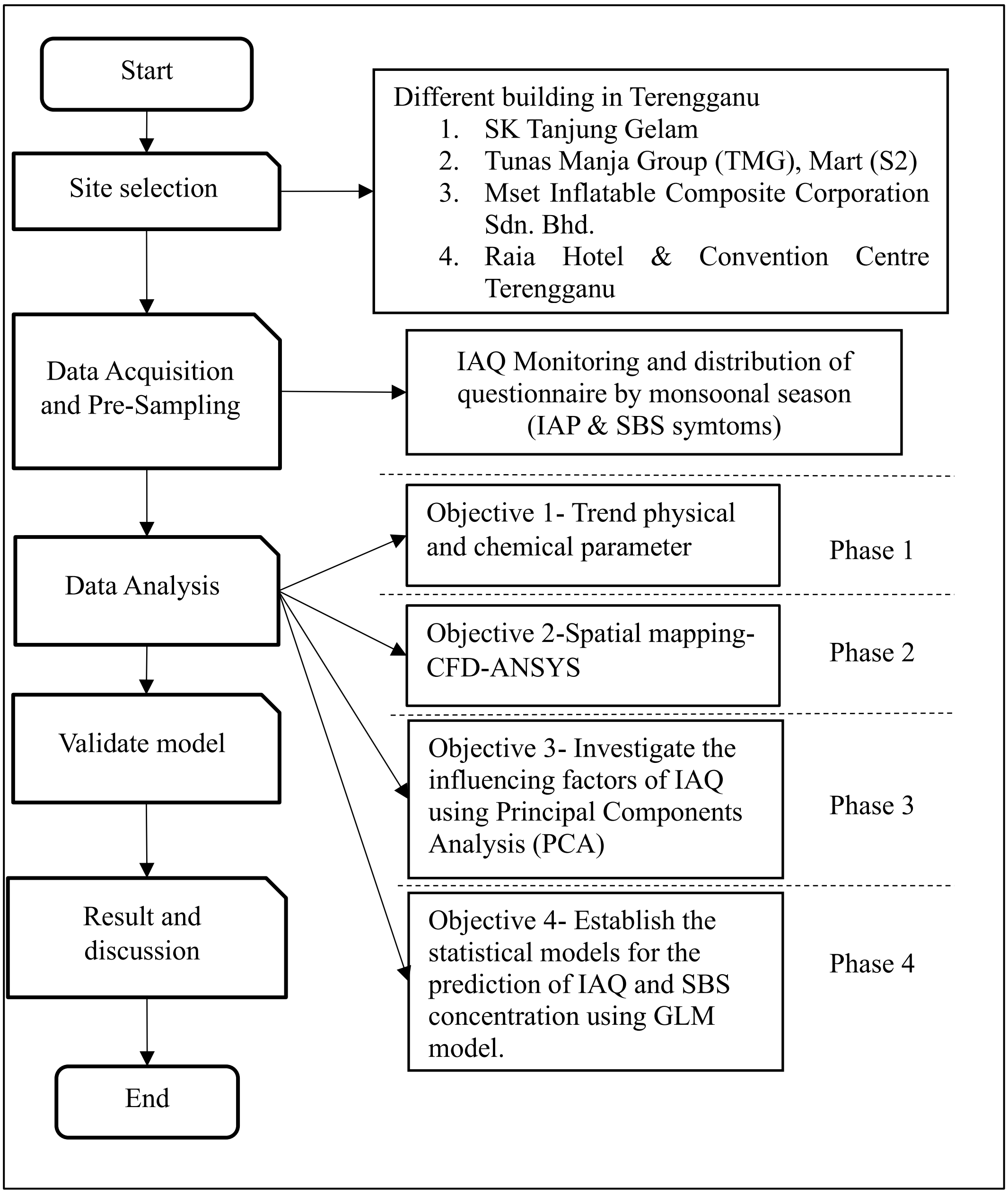


Figure 3.1 Overview of research flowchart

3.2 Site Selection

The NEM, SWM, and two shorter transitional monsoon seasons can all be identified based on these variations (Abdullah *et al.*, 2020; Meteorologi Malaysia., 2020). In Peninsular Malaysia, the NEM, which runs from November to March, and the SWM, which runs from May to September, typically impact the east coast state of Malaysia, especially Terengganu (Othman *et al.*, 2022; Ismail *et al.*, 2020). Since the South China Sea borders Terengganu, the NEM significantly impacts the state's economy by bringing storms and heavy rainfall, which can directly affect Terengganu's economic sectors due to most of the workers or occupants spending time indoors and high risk of exposure to poor IAQ (Arsad *et al.*, 2023; Meteorologi Malaysia., 2020). Increased humidity during NEM can increase IAP, and airborne allergens can lead to poor air quality, harming occupants' respiratory health (Isa *et al.*, 2022). Since the NEM brings high humidity, which can promote mold growth, dust mites, and mildew, it negatively affects indoor air quality (IAQ) compared to SWM (Abdel-Salam., 2021). During both monsoonal seasons, monitoring indoor air quality (IAQ) within the building sector of the Terengganu economy was crucial for assessing indoor air quality and understanding how occupants responded to the SBS symptoms. The assessment of indoor air quality (IAQ) among employees is essential for various reasons, broadly classified into three categories: health, productivity, and economic consequences (Pawankar *et al.*, 2020). Services accounted for 52.7% of Terengganu's GDP in 2021, with manufacturing coming in second with 34.9% (DOSM, 2022). Services sectors contain three dominant sub-economies, also known as subsectors, which consist of wholesale and retail trade (17.8%), education (15.3%), and hospitality (12%) in 2021 (DOSM, 2022). Study areas are determined by the dominant sectors that contribute to the economy of Terengganu. The school (teacher's room) at Sekolah Kebangsaan Tanjung Gelam represented the education subsector. In contrast, wholesale and trade were represented by TMG Mart, hospitality by Raia Hotel & Convention Centre Terengganu, and manufacturing, boat building manufacturing by Mset Inflatable Composit Corporation Sdn. Bhd.

3.2.1 Site Selection Procedure

Acquiring authorization from regulatory bodies, property owners, or managers was mandatory. The research was conducted only after the necessary consent was obtained from individuals or groups impacted by the assessment, mainly if it involved personal data or potentially disruptive occupants (Hishamuddin *et al.*, 2022). The ever-increasing necessity for a representative statistical sample in scientific studies has generated the demand for an effective method of determining sample size. Krejcie and Morgan (1970) developed a table to determine the sample size for a specific population and the minimum sample size of 10 (Uakarn *et al.*, 2021). This was done in order to address the extant gap. The IAQ monitoring process must be initiated when the number of occupants must exceed 10 (N=10) (Amzah & Wahid, 2024).

Permission was requested from 29 primary schools in Kuala Nerus, Terengganu, based on the local educational portal list (PPDKN, 2022). Permission to conduct IAQ monitoring in the teacher's room was obtained through a walk-in, direct call to the school office, email, and a letter requesting permission. Only one school, Sekolah Kebangsaan Tanjung Gelam (S1), granted this request, and site one was obtained to represent services sectors with subsector education. Sectors and subsectors refer to the dominant economy and sub-economy terms. Plenty of business in Terengganu involved wholesale and retail trade, but the number of occupants or workers was insufficient. A supermarket that sells groceries to consumers is included in wholesale and trade sub-sectors. Four potential supermarkets were located in Kuala Nerus, Terengganu. A letter to request permission to conduct IAQ monitoring was given, and only Tunas Manja Group (TMG) Mart (S2) was permitted to conduct IAQ monitoring for both monsoonal seasons. Manufacturing sectors specified manufacturing, transport equipment, and repairs (DOSM, 2022). The boat-making manufacturing industry is one of the established manufacturing sectors in Terengganu due to the many specialists in boat-making gatherings in Terengganu, Malaysia, and Indonesia (Ali, 2022). The adequacy of occupants or workers inside the building was determined before requesting permission during walk-ins and direct calls to potential companies. Managers or regulatory bodies requested a letter of permission by walk-in after making an appointment at Mset Inflatable Composite Corporation Sdn. Bhd. (S3). Companies granted permission. The last sector is services with sub-sectors hospitality. Five hotels and resorts had a response number of workers. They were suitable for IAQ monitoring, but only one hotel was permitted to do so in their lobbyists and offices, Raia Hotel & Convention Centre Terengganu (S4).

The location of study areas is shown in Figure 3.2, which shows the location of each study area; it is essential to plan transportation and movement of sampling to avoid unexpected events. After getting permission from the property owner to run IAQ monitoring, this study determines the sampling point and duration for which time interval to run pre-sampling or pilot test at each study area, as shown in Table 3.1. Table 3.1 shows the study areas' characteristics used as a reference to replicate the sampling for both monsoonal seasons that consists of the sampling date, pre-sampling date, time interval, sampling point, longitude, and latitude of each study area. Table 3.1 shows S1 has eight sampling points with 5-minute intervals, seven inside the teacher's room and one ambient air or outdoors. S2 consists of 10 sampling points (9 indoors; 1 outdoors) with 6-minute time intervals, and the IAQ monitoring takes place from 0900 to 1700 hours for both monsoons. S3 consists of 7 sampling points, six indoor and one outdoor sampling point for pre-sampling and during data collection for SWM and NEM. S4 has 12 sampling points indoors and one sampling point outdoors. S4 has 5-minute intervals, and IAQ monitoring was conducted between 08830 and 1630 hours. Sampling point was conducted based on ICOP-IAQ 2010 guidelines which the recommended minimum number of sampling points for indoor air quality assessment depends on the total floor area served by a mechanical ventilation and air-conditioning (MVAC) system. The guidance can be broken down as follows which stated in TableA4-1 (ICOP-IAQ 2010):

1. For areas less than 3,000 m²: A general rule of 1 sampling point per 500 m² is recommended. This ensures sufficient coverage for smaller spaces while maintaining a reasonable balance between accuracy and practicality.
2. For areas between 3,000 m² and 5,000 m²: A minimum of 8 sampling points is recommended to adequately represent the air quality conditions in this mid-sized space.
3. For areas between 5,000 m² and 10,000 m²: The number of sampling points increases to a minimum of 12 points, reflecting the need for more measurements in larger spaces to account for variability.

4. For areas between 10,000 m² and 15,000 m²: A minimum of 15 sampling points is required. As the area grows, more sampling points help capture differences in air quality across various zones.
5. For areas between 15,000 m² and 20,000 m²: The recommended minimum increases to 18 sampling points, ensuring sufficient data is gathered for larger environments.
6. For areas between 20,000 m² and 30,000 m²: A total of 21 sampling points is advised to provide adequate spatial coverage and representation of indoor air quality.
7. For areas greater than or equal to 30,000 m²: A broader rule of 1 sampling point per 1,200 m² is applied. This reflects the logistical challenge of assessing very large areas while balancing coverage and practical resource allocation.

In summary, the number of sampling points increases proportionally with the floor area to ensure that air quality is assessed comprehensively. Smaller spaces use a "per area" ratio, while larger spaces transition to a specific number of points for practical efficiency. This method ensures reliable air quality evaluation across different building sizes. However, depending on the type and nature of the buildings, additional samples should be taken if it is considered necessary

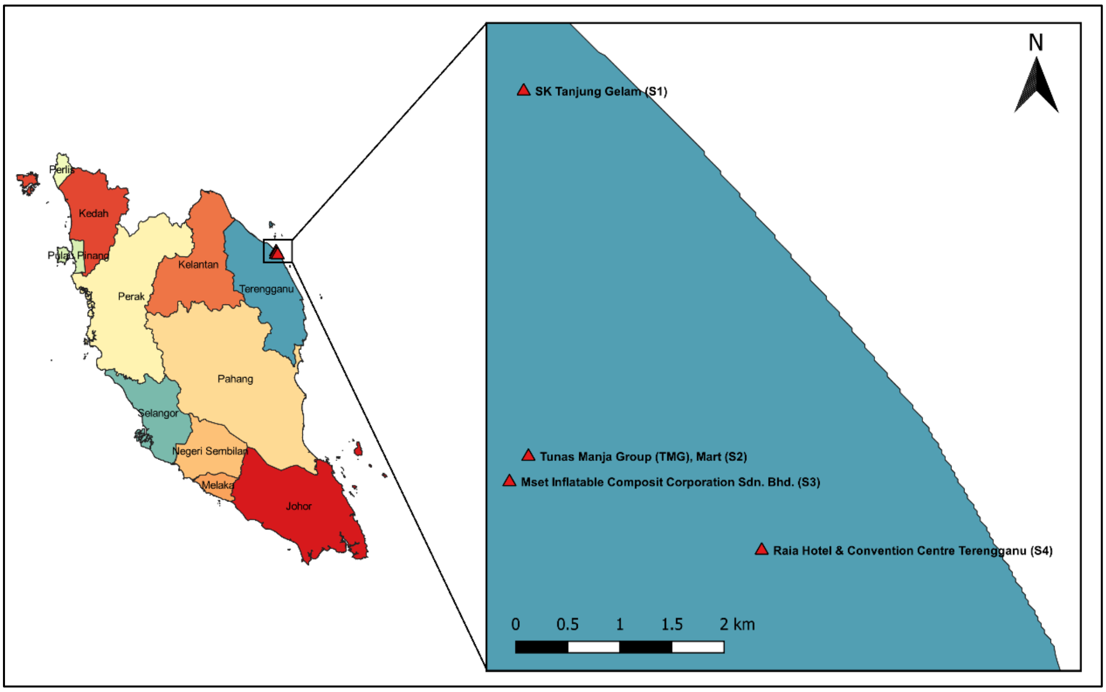


Figure 3.2 Location of study area

Table 3.1 The study area classification is based on the sectors and subsectors, the number of sampling points, the duration of sampling, the sampling date, the pilot test or pre-sampling date, the monsoon, the longitude and latitude.

Location	Sector, subsector	Sampling points	Duration	Sampling Date	Pre-sampling Date	Monsoon	Longitude/Latitude
SK Tanjung Gelam (S1)	Services, Education	8 points (7 indoors, one outdoor)	5 minutes interval (8 am-3 pm)	5 Feb 2023- 16 Feb 2023	20 Feb 2023	NEM	103° 4'50.64"E 5° 24'46.89"N
				11 Sept 2022- 22 Sept 2022	25 Sept 2022	SWM	
Tunas Manja Group (TMG), Mart (S2)	Services, wholesale, and retail trade	10 points (9 indoors, one outdoor)	6 minutes time interval (9 am-5 pm)	19 Feb 2023- 2 March 2023	7 March 2023	NEM	103° 4'52.13"E 5° 22'53.06"N
				21 May 2023- 1 June 2023	5 June 2023	SWM	
Mset Inflatable Composit Corporation Sdn. Bhd. (S3)	Manufacturing, transport equipment, and repairs.	7 points (6 indoors, one outdoor)	10 minutes time interval (8.30 am-5.30 pm)	21 Nov 2022- 2 Dec 2022	6 Dec 2022	NEM	103° 4'46.21"E 5° 22'45.13"N
				7 May 2023- 18 May 2023	23 May 2023	SWM	
Raia Hotel & Convention Centre Terengganu (S4)	Services, Hospitality	13 (12 indoors, one outdoor)	5 minutes time interval (8.30 am-4.30 pm	5 March 2023- 16 March 2023	20 March 2023	NEM	103° 6' 4.863" E 5° 22' 23.8002" N
				4 June 2023- 15 June 2023	19 June 2023	SWM	

SWM-Southwest Monsoon; NEM- Northeast Monsoon

3.3 Data Acquisition and Pre-Sampling

Data acquisition was conducted from September 2022 until June 2023. The IAP were measured using instruments borrowed from Fluid Lab, Universiti Malaysia, Terengganu. IAP consists of ventilation performance indicator (carbon dioxide, CO_2), chemical parameters (total volatile organic compound, TVOC; formaldehyde, HCHO; carbon monoxide, CO; respirable suspended particulate, RSP), and physical parameters (air movement, AM; temperature, T; relative humidity, RH). Figure 3.3 shows the instruments used for data collection. Figure 3.3, from the left in the first row, shows the TSI Climomaster Model 9545, DustTrax DRX Aerosol Monitor 8533, and Q-Trak Indoor Air Quality Monitor 7575. View from the left in the second row showing Formaldehyde meter and Portable VOC Monitor MiniRae 30000.

TSI Climomaster Model 9545 measured physical parameters such as temperature, relative humidity, and air movement. This instrument is equipped with a straight telescopic probe. Optimal for optimizing HVAC system performance, commissioning, plant maintenance, critical environment certification, and duct traverses. Range probe for TSI Climomaster Model 9545 range for velocity or air movement between 0-30 m/s, temperature range between -10 to 60^{o}C, relative humidity probe range between 5 to 95% (Alwi et al., 2021; Nazli et al., 2023). This meter utilizes a single probe with multiple sensors to measure and record multiple parameters simultaneously. Dust Trak DRX Aerasol Monitor 8533 was used to measure RSP, as shown in Figure 3.3. Both mass and size fractions can be measured simultaneously by the DustTrak™ DRX Aerosol Monitor 8533. The DustTrak DRX desktop monitor is a multi-channel, battery-operated, data-logging, light-scattering laser photometer that captures a gravimetric sample and provides real-time aerosol mass readings range 0.001 to 150 mg/m^3(Singh *et al.*, 2023). It is appropriate for various outdoor applications, harsh industrial environments, construction and environmental sites, and clean office settings (Branco *et al.*, 2024). The DustTrak DRX monitor monitors aerosol contaminants, including smoke, vapors, mists, and dust. Q-Trak Indoor Air Quality Monitor 7575 Figure 3.3 was the last instrument in the first-row view from the left, simultaneously displaying CO_2 (reading range between 0-5000ppm) and CO (reading range 0 to 500 ppm). This instrument is equipped with a straight telescopic probe.

The second-row view from the left for Figure 3.3 shows the Formaldehyde meter. The formaldehyde meter is equipped with an electrochemical sensor that accurately and precisely measures the concentration of formaldehyde gas in real-time, following the acceptance criteria of the U.S. National Institute for Occupational Safety and Health (NIOSH) with range 0-30 ppm (Law *et al.*, 2024; Lu *et al.*, 2024). The last figure from the second-row view from the left was Portable VOC Monitor MiniRae 30000, which measured total volatile organic compound concentration (TVOC). The MiniRAE 3000 + is a comprehensive handheld VOC (Mainka *et al.,* 2018) monitor that employs a third-generation patented PID technology to measure one of the highest levels of ionizable compounds precisely (Feng *et al.*, 2023). It comprehensively measures VOCs within the 0 to 15,000 ppm range. These five instruments must position the inlets of samplers at a height of 75 to 120 cm, at least 1 meter from localized sources, and not within 2 meters of doors during data acquisition (Abas *et al.*, 2021). The instruments must be positioned to minimize the interruption of work activities within the study area while representing the workstation layout and work activities (Zubir *et al.*, 2022).

View from the left in the first row showing TSI Climomaster Model 9545, Dust Trax DRX Aerosol Monitor 8533 and Q-Trak Indoor Air Quality Monitor 7575.

View from the left in the second row showing Formaldehyde meter and Portable VOC Monitor MiniRae 30000

Figure 3.3 Instruments used for data collection

After determining the instruments used for IAQ monitoring, the next step is pre-sampling or pilot test. Pre-sampling or pilot testing is an initial test or a miniature version of a larger-scale study or activity. The term "pilot" refers to testing a plan, initiative, or other strategy before conducting the sampling for data collection (Deng *et al.*, 2023). Collecting an overview of the study area shown in Tale 3.2 is essential. Indoor characteristics measured and observed during pre-sampling were study area dimensions, level of the study area room, and mechanical ventilation, such as the number of ceiling fans, windows, doors, and air conditioning. Besides that, traffic conditions, building age, and building materials were noted for worst-case scenarios during sampling time, number of occupants, and operating hours.

Pre-sampling or pilot tests are essential for questionnaire distribution (Dhungana & Chalise, 2020). It is crucial to determine whether occupants or workers understand the questionnaires given to them and proceed with Cronbach's alpha after running a pilot test for the SBS symptoms questionnaire. Cronbach alpha is a reliability coefficient used to assess the internal consistency of tests and measures (Amzah & Wahid, 2024). The complete questionnaires, particularly those used for data collection and after checking reliability from the pilot test or pre-sampling questionnaires, can be found in Appendix A

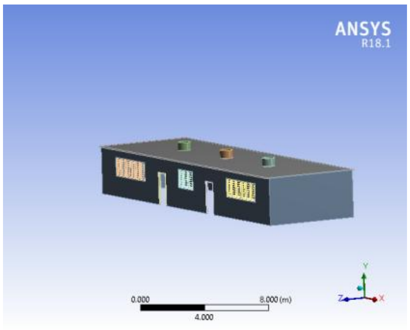
The layout of the study area is crucial in determining the appropriate sampling points to ensure accurate and reliable data collection, while also preventing replication mistakes during the sampling cycle. This layout serves as a reference for subsequent monsoonal seasons, allowing for consistent determination of IAQ sampling points at each study area. Figure 3.4 illustrates the specific layouts for each study location. Figure 3.4 a) shows the layout for Sekolah Kebangsaan Tanjung Gelam (S1), where the sampling is conducted in the teacher’s room. Figure 3.4 b) represents Tunas Manja Group (TMG) Mart (S2), focusing on the supermarket area. Figure 3.4 c) depicts Inflatable Composit Corporation Sdn. Bhd (S3), with sampling points located within the manufacturing area. Figure 3.4 d) outlines the layout for Raia Hotel & Convention Centre Terengganu (S4), targeting the office and lobby areas.

Additionally, the figures include the number of sampling points at each location, ensuring the sampling covers various zones within the buildings. Figure 3.4 e), f), g), and h) illustrate the specific number and locations of sampling points for S1, S2, S3, and S4, respectively. The positioning of these points is based on the suitability concerning the movement and activities of the occupants and workers within each building. The selection of sampling locations adheres to the guidelines provided in ICOP-IAQ 2010, ensuring that the sampling points are representative of the typical environmental conditions in the respective areas. This strategic placement aims to capture a comprehensive overview of the IAQ across different zones, thereby facilitating accurate assessment and comparison of air quality during different monsoonal periods.

Table 3.2 Overview of ventilation in study areas

Characteristics	S1	S2	S3	S4
Location of study area	Teachers room	Supermarket	Manufacturing area	Office & lobby
Study area dimension	Area: $126m^2$ Volume: $378m^3$	Area: $880m^2$ Volume: $2640m^3$	Area: $800m^3$ Volume: $5600m^3$	Area: $583.5m^2$ Volume: $3177m^3$
Level	4	1	1	1
Windows	21	-	-	-
Doors	2	2	3	2
Ceiling fans	3	-	-	-
Air Conditioning (operating)	-	4	3	3
Ventilation system	Open	Closed	Open	Closed
Building age	>10 years	>10 years	>10 years	>10 years
Building material	concrete	concrete	concrete	concrete
Background location	Background	Industrial	Industrial	Residential
Traffic condition	Heavy traffic during the beginning and end of school sessions	Heavy traffic during peak hours	Traffic light conditions on most times	Heavy traffic during lunch hours
Operation hours	7:00 AM-3:00 PM	8:00 AM- 10:00 PM	7:30 AM- 6:30 PM	7:30 AM-7:30 PM
Number of occupants	11	33	16	18

a)



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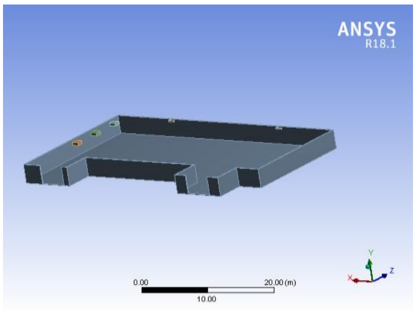

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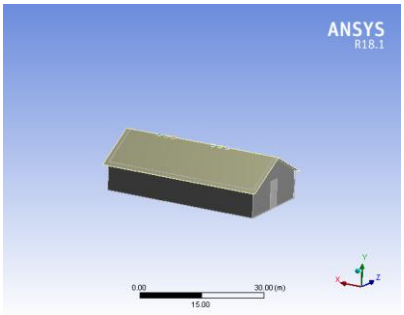

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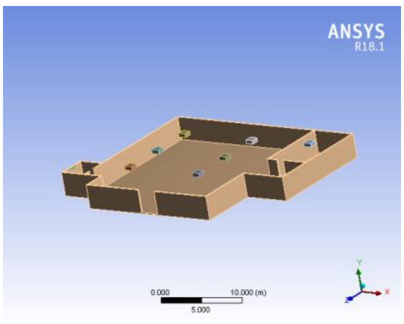

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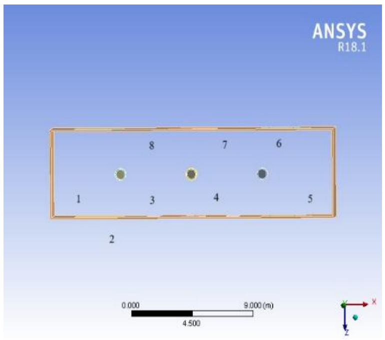
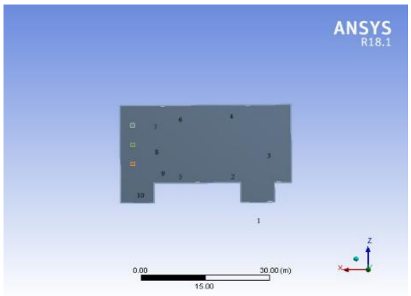
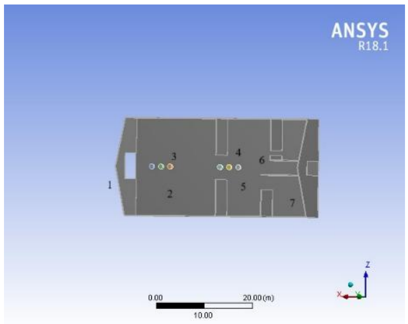


f)



g)



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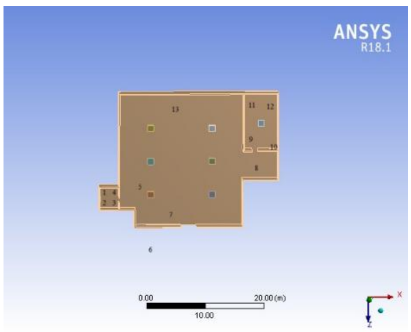


Figure 3.4 a) Layout for S1; b) Layout for S2; c) Layout for S3; d) Layout for S4; e) number of sampling point for S1; f) number of sampling point for S2; g) number of sampling point for S3; h) number of sampling point for S4

3.4 Data Analysis

Data analysis was divided into four phases and used different types of analyses

3.4.1 Status of Indoor Air Quality (IAQ) and Sick Building Syndrome (SBS) symptoms

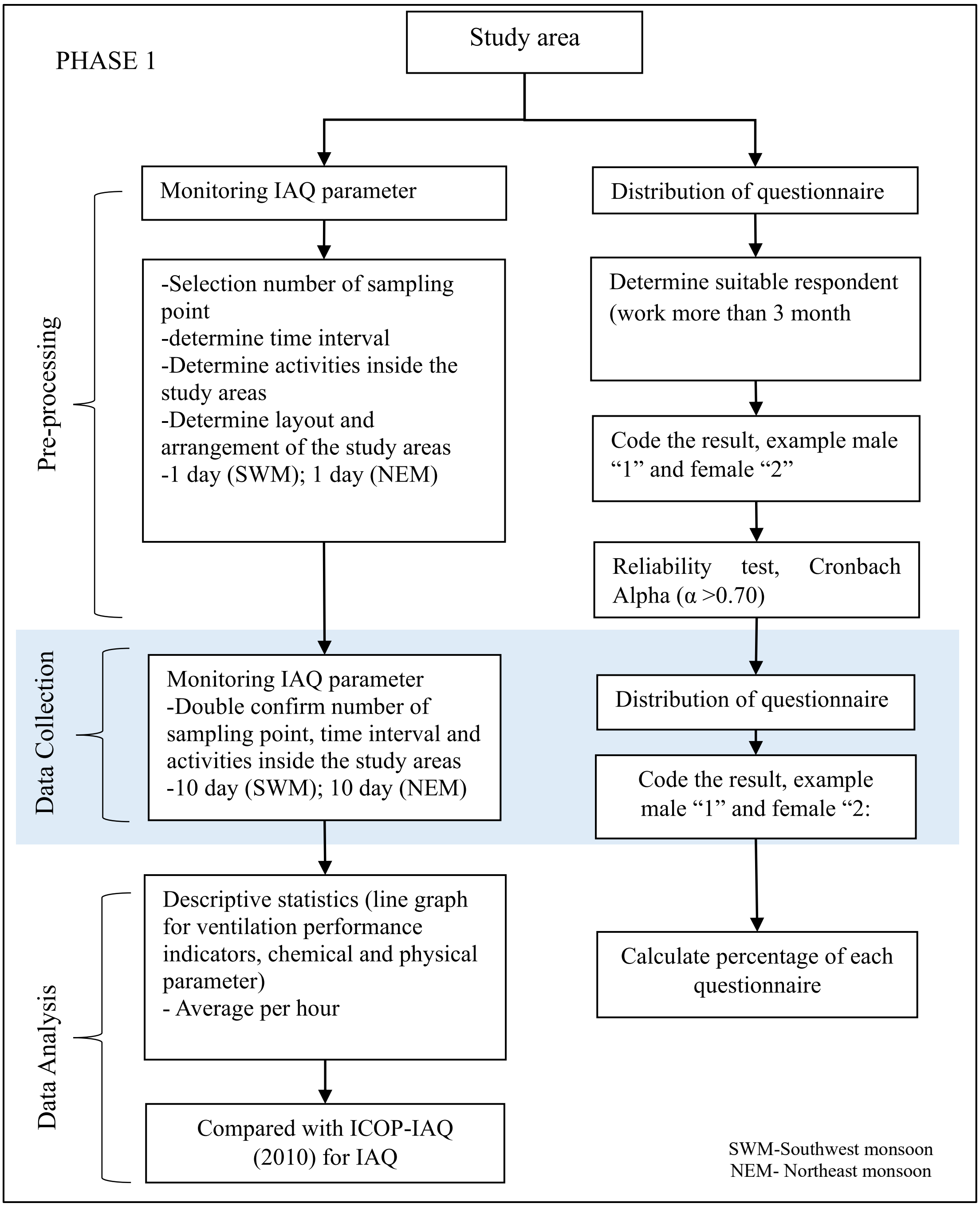


Figure 3.5 Flow chart for Phase 1

Figure 3.5 shows the overall process for phase 1 from the pre-processing, data collection, and data analysis stage. The pre-processing stage in this study consists of a pre-sampling or pilot test method for IAQ monitoring and distributing the questionnaire, as stated in section 3.3, for 1 day in each study area for both monsoons. IAQ monitoring pre-processing includes determining the number of sampling points that follow guidelines for sampling IAQ besides determining activities inside the buildings and determining the layout of the study area during pre-sampling or pilot tests and the position of the instruments. Pre-sampling was conducted one day for SWM and NEM. The questionnaires were distributed after IAQ monitoring because most occupants or workers needed further explanation about the question that needed to be answered. Then, the answers from the questionnaire are coded into the Statistical Package for Social Sciences (SPSS). This process needs to convert the data collected in questionnaires into numerical and make it easier to calculate. After that, the questionnaire was proceeded using Cronbach's Alpha. Cronbach's alpha tests to see if multiple-question Likert-scale surveys are reliable (Kim *et al.*, 2019). These questions measure latent variables—hidden or unobservable variables like a person's conscientiousness, neurosis, or openness. These are very difficult to measure in real life. Cronbach's alpha will tell you how closely related a set of test items are as a group in each item that questions in questionnaires. The acceptable range for Cronbach's Alpha is more than 0.70 (Bell *et al.*, 2022; Mamat *et al.*, 2020). Equation 1 shows the equation of Cronbach's Alpha.

$$\alpha = \frac{N \cdot \bar{c}}{\bar{v} + (N-1) \cdot \bar{c}} \tag{1}$$

N is the number of items, $\bar{c}$ is average covariance between item-pairs and, $\bar{v}$ is average variance.

The process in phase 1 proceeds with data collection. As shown in Table 3.1, the sampling date for all four study areas was selected with the same sampling point for 10 days during the SWM and 10 days during the NEM. The sampling methods and instruments used were explained in detail in the section on data acquisition.

Descriptive analysis is a fundamental component in helping to analyse the data. It is used as brief descriptive coefficients that summarise the data set, representing the entire number of samples. Several descriptive statistics are evaluated in this study, such as the mean for IAP and percentage for Sick Building Syndrome Symptoms (SBS) symproms questionnaires. IAP means value, known as the average number, which compares with the standard introduced in the ICOP-IAQ (2010). Statistical distribution measures, also known as descriptive statistics or summary statistics, are used to summarise the information from collected or set of data, and equations 1 showed equations for the mean (Anh *et al.*, 2024; Mansor *et al.*, 2024; Mansor *et al.,* 2023)

Mean

To compute the mean, (X), the summation of the total value, ($\sum x$), divided by the total number of samples, (n), as in the following Equation (2);

$$X = \frac{\Sigma x}{n} \tag{2}$$

X is a sample mean, $\sum x$ is the sum of scores in a distribution and n is = the number of samples.

Percentage

To compute percentage (%), divide the numerator (number on the top) by the denominator (number on the bottom) and multiply by 100.

$$\% = \frac{numerator}{denominator} \times 100 \tag{3}$$

% is a percentage. The numerator is the total sample obtained, and the denominator is the sum of the samples.

The trend line displays the mean value for IAP, which consists of ventilation performance indicators and physical and chemical parameters. The mean was then compared with standard ICOP-IAQ 2010. The trend of IAP is displayed on the trend line in Microsoft Excel, and the questionnaire was analysed using SPSS.

3.4.2 Spatial mapping of the study area using the computational fluid dynamic (CFD)

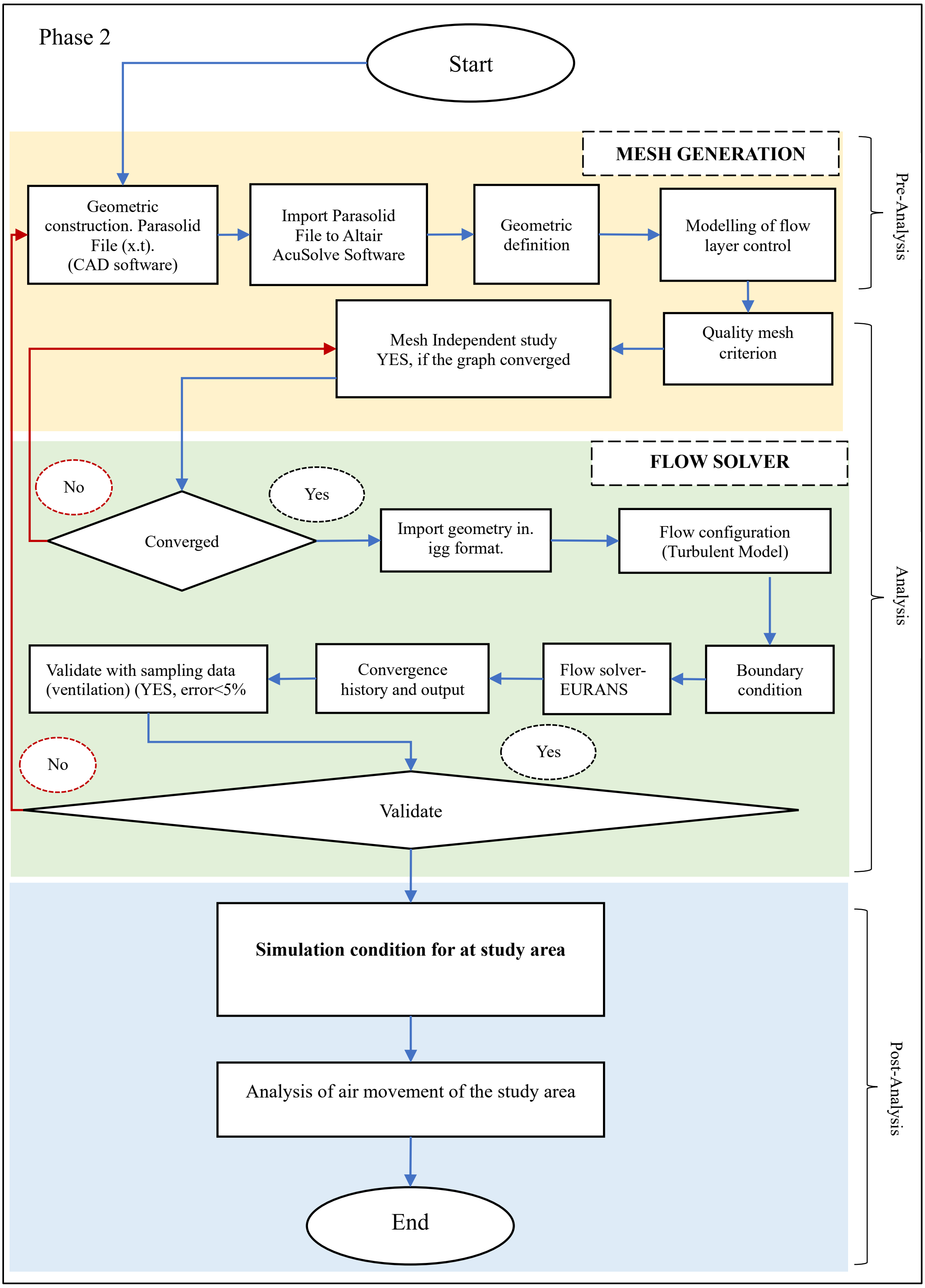


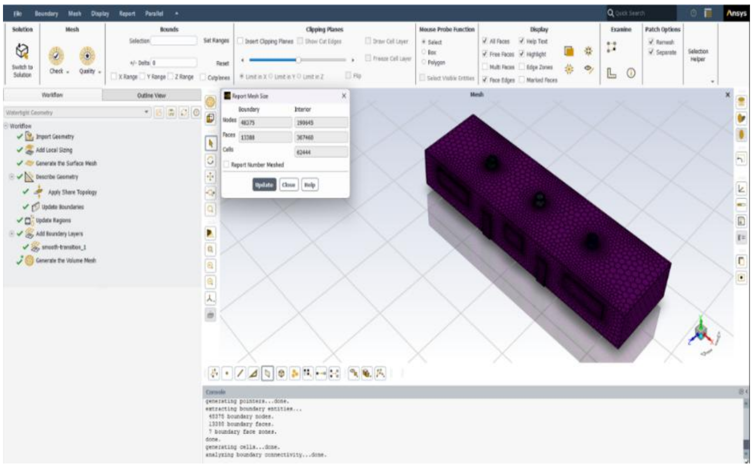
Figure 3.6 Flow chart Phase 2

Phase 2 started with a pre-analysis stage, which focused on meshing generation. Based on computing cost and accuracy, the mesh with a high meshing number was chosen for the remaining simulation scenarios. CFD simulation's accuracy depends on precise meshing. The procedure entails the following steps: defining the problem domain, selecting and generating the mesh, refining and verifying the mesh, and establishing the boundary and initial conditions for the simulation. It is essential to conduct mesh independence studies and ensure high mesh quality to obtain reliable results, and the process proceeds with analysis and post-analysis as shown in Figure 3.6. Increasing the mesh number shows the relative error in the anticipated airflow of pollutants, and this study focused on RSP. The mesh comprises fundamental building blocks known as elements or cells (Anyaegbuna *et al.*, 2024). A mixture of these components, including pyramids, hexahedra, and tetrahedra, constitutes the lattice. Figure 3.7 shows meshing for each study area and the node number for S1, S2, S3, and S4. Sekolah Kebangsaan Tanjug Gelam (S1) show the nodes number in Figure 3.7 a) was 48375. Figure 3.7 (b) shows the number of nodes for TMG Mart (S2) was 24605, and Figure 3.7 (c) shows the node number was 123149 for Mset Inflatable Composit Corporation Sdn. Bhd. (S3). Raia Hotel & Convention Centre Terengganu (S4) meshing is shown in Figure 3.7 (d) with the number of nodes 33090.

Mesh generation was located at the pre-analysis stage. Geometric construction is frequently executed in Computational Fluid Dynamics (CFD) and other engineering applications using CAD (Computer-Aided Design) software to generate and modify the domain's 3D models (Hatif *et al.*, 2024). The Parasolid file format, identified by the .x_t extension, is widely used in CAD systems. Autodesk Inventor is an example of CAD software that supports Parasolid and can be used to generate a Parasolid file. If it is necessary to work with pre-existing models, importing Parasolid files into these applications is also possible. The software enables the construction of geometric shapes (e.g., cylinders, spheres) and the execution of operations, such as extrusion and revolution, to generate intricate geometries when a model is generated in CAD software (Ejaz *et al.*, 2024). After creating or modifying the geometry, it can be saved or exported as a Parasolid file (.x_t) for subsequent analysis or use in other software. Importing a Parasolid file into Altair AcuSolve typically involves a series of stages to guarantee that the geometry is accurately imported and prepared for meshing and simulation

(Silfwerbrand, 2020). Altair AcuSolve is a robust CFD solver that does not explicitly support Parasolid files. However, importing and working with Parasolid files is possible using Altair's pre-processing tools, such as Altair HyperMesh. Verify the precision and comprehensiveness of the imported geometry. Then, the process proceeds with inspecting the geometry to ensure no gaps, overlaps, or errors (Ganesh *et al.*, 2020). Utilize the tools provided by HyperMesh to rectify any deficiencies in the geometry. This may involve the reduction of spaces, the elimination of duplicate surfaces, or the simplification of intricate shapes. The procedure proceeds with predetermined mesh parameters, including refinement criteria, mesh type (structured or unstructured), and element size. Utilise HyperMesh's meshing tools to produce a computational mesh derived from the imported geometry. Ensure that the geometry is of high quality and appropriate for CFD analysis, then evaluate the mesh for quality metrics, including orthogonality, aspect ratio, and skewness (Aljuhaishi *et al.*, 2024). After the simulation, use post-processing tools to analyse the results and validate your findings. Altair HyperMesh is an intermediary application that manages geometry and mesh generation when importing a Parasolid file into Altair AcuSolve. Initially, the Parasolid file is imported into HyperMesh, the geometry is cleaned and prepared, the mesh is generated, and the mesh is exported in a format compatible with AcuSolve. After that, you import the mesh into AcuSolve, configure your simulation, and execute the analysis. This workflow guarantees that the geometry and mesh are appropriately prepared for precise CFD simulations (Roslan *et al.*, 2023). The accuracy of the CFD results depended on meshing process generation; the primary step involved assessing the RSP movement—the grid independence analysis's simulation findings in the study area. The computational mesh was improved until the respirable suspended particulate (RSP) flow could be predicted with an acceptable error between two successive meshes.

a)



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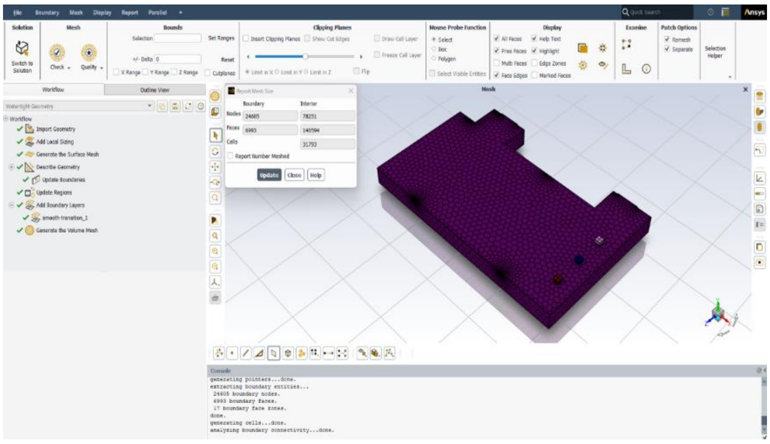

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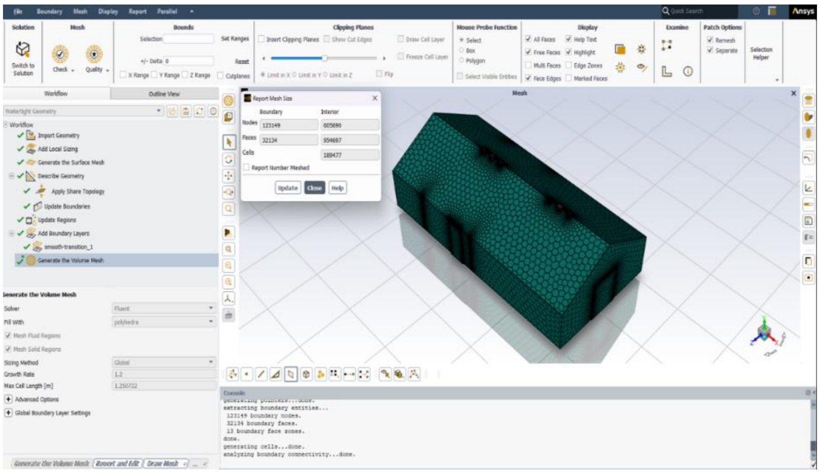

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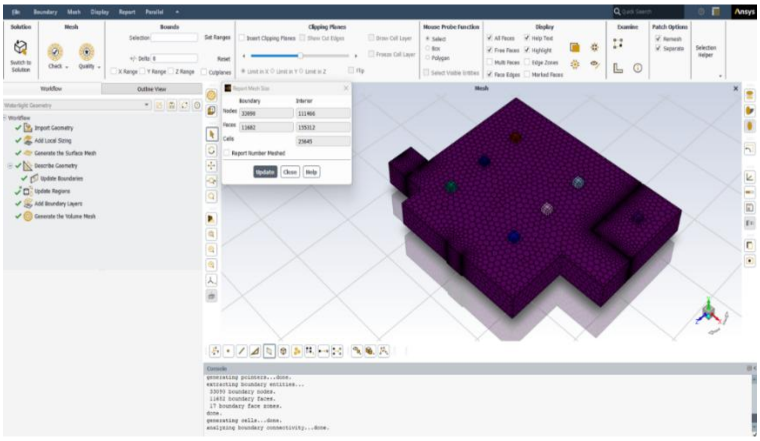

Figure 3.7 a) Meshing in the study area for Sekolah Kebangsaan Tanjung Gelam (S1). b) Meshing in the study area for TMG Mart (S2). c) Meshing in the study area for Mset Inflatable Composit Corporation Sdn. Bhd. (S3).d) Raia Hotel & Convention Centre Terengganu.

Before proceeding with the simulation step the dataset was split into 9 days for model simulation and 1 day dataset for validation process. The analysis stage contains flow solver analysis and setup. The flow solver step in ANSYS CFD entails the following steps: the simulation is established, the solver settings are configured, the simulation is executed, and the results are analysed. The procedure entails the following steps: the preparation of the geometry and mesh, the definition of physical and boundary conditions, the selection and configuration of the solver, and the execution of post-processing to interpret the results. This workflow guarantees that the fluid flow simulation is precise and dependable and offers valuable insights for design and analysis. In ANSYS CFD (such as ANSYS Fluent, managing the entire workflow, from importing geometry to validating results, involves several steps. Here is a detailed explanation of each step in importing geometry in IGES format, setting up the flow configuration with a turbulence model, defining boundary conditions, running the flow solver with EURANS, checking convergence history, and validating results with data. The first step in this process was to import Geometry in IGES Format in ANSYS Workbench. Launch ANSYS Workbench by starting the ANSYS Workbench environment, the central platform for managing the simulations. Then, add a CFD Analysis System by dragging and dropping by clicking "Fluid Flow (CFD)" analysis system from the toolbox into the Project Schematic and double-click on the “Geometry” cell to open the associated geometry preparation tool then import the IGES File in Ansys

Design Modeler then inspect the imported geometry for any issues like gaps, overlaps, or errors (Marashian *et al.*, 2023). Use the available tools to fix any issues involving merging surfaces, closing gaps, or simplifying complex geometry.

Next, flow configuration with a turbulence model is done by choosing the suitable model. There are two types of models: k-epsilon (k-ε) and k-omega (k-ω). The Standard Renormalization Group (RNG) is k-ε, which is realizable and suitable for general turbulence modeling, and k-ω was Shear Stress Transport (SST) and used for better flow with boundary layered adverse pressure gradients (Sachdeva, 2022). This study chooses k-ε in the geometry setting for all study areas due to the model's capability to handle free-stream and detached flow better than k-ω (Babaoglu *et al.*, 2020). The process proceeds with configuring specific parameters for the turbulence model as required. This process presents a flow to conduct a sensitivity analysis of different door gap sizes, solar intensities, and the number and orientation airflow involving air movement and respirable suspended particulate (RSP) variations. The CFD model of the floor was validated based on field measurements (Cheng *et al.*, 2021). This study used FLUENT to conduct unsteady-state CFD simulations (Nandan *et al.*, 2020). The SIMPLE algorithm was adopted for pressure-velocity coupling (Kwok *et al.*, 2020; Chen *et al*., 2020). A second-order upwind scheme was used for both convection and viscous terms.

The analysis proceeds with the third step, defining boundary conditions. In ANSYS Fluent, go to the Boundary Conditions section, select each boundary (e.g., inlet, outlet, walls), and define conditions such as respirable suspended particulates (RSP) concentration, air movement, or temperature. The next step is proper initialization. Proper initialization helps the solver converge to a stable and accurate solution more effectively. ANSYS Fluent offers two primary methods for initialization: Standard Initialization and Hybrid Initialization (Cheng *et al*., 2020). This study used to initialize the flow by choosing Hybrid Initialization rather than Standard Initialization. Hybrid initialized chosen because it is more advanced, and the adaptive initialization method is designed to improve convergence, especially for complex geometries and turbulent flows. Besides, it can help achieve faster and more stable convergence, particularly in complex simulations with intricate geometries or turbulent flows. It can provide a more accurate starting point for the solver by considering local flow features and initial guesses.

The fifth step consists of a flow solver. The term EURANS (Enhanced Unsteady Reynolds-Averaged Navier-Stokes) refers to a type of turbulence modelling approach used to improve the prediction of turbulent flows, particularly in simulations involving unsteady or complex flow conditions. EURANS is an advanced variant of the traditional Reynolds-Averaged Navier-Stokes (RANS) models, and this study used EURANS setup for the simulation. EURANS is designed to address some of the limitations of standard RANS models by improving the accuracy of turbulence predictions in unsteady or complex flow conditions. It combines elements of both RANS and Large Eddy Simulation (LES) approaches to offer enhanced performance. EURANS is an advanced turbulence modelling approach extending the traditional RANS framework to handle better unsteady and complex flow scenarios (Deb *et al.*, 2022; Belotti *et al.*, 2020). By incorporating additional terms and considerations for transient effects, EURANS improves the accuracy of turbulence predictions in CFD simulations. In ANSYS CFD software, configuring EURANS involves selecting appropriate turbulence models, enabling unsteady effects, and setting up transient simulations. This approach is particularly useful for applications where capturing the dynamic behaviour of turbulent flows is critical for accurate results (Berville *et al.*, 2021).

After selecting a flow solver, the next step was to monitor its convergence history and output. Check the residuals in ANSYS Fluent to observe their convergence for continuity, momentum, and other equations. Review the convergence history plots to ensure that residuals decrease, and the solution converges (Silva, 2023). Adjust solver settings or refine the mesh if convergence issues are encountered (Morawska *et al.*, 2017). Then, save the simulation results and data files for post-processing and analysis and generate detailed reports, including convergence history, solution summary, and other relevant information.

The last step is validating results and sampling data by comparing them with experimental data. Compare simulation results with experimental or benchmark data to ensure accuracy and check the sensitivity of results to changes in mesh size, boundary conditions, or model parameters (Mohammad & Calautit, 2021). Details of the mathematical formulation for the flow solver are explained in detail in the mathematical formulation section below. Compare simulation results with sampling data by calculating the percentage error between simulation results and sampling data using the formula in Equation (4)

$$Error\ (\%) = \left|\frac{Simulation\ results - Sampling\ Data}{Sampling\ data}\right| \times 100 \tag{4}$$

3.4.3 Mathematical formulations

The cornerstone of computational fluid dynamics is the fundamental governing equations of fluid dynamics-the continuity, momentum, and energy equations. These equations speak physics line (Kwok *et al.*, 2020). They are the mathematical statements of three fundamental physical principles upon which all of fluid dynamics is based on:

i. Mass is conserved.
ii. Newton's Second Law
iii. Energy is conserved.

Newtonian fluid without free-surface effects, the equations of motion are the continuity equation (4) and Navier-Stokes equations (5).

$$\vec{\nabla} \cdot \vec{V} = 0 \tag{5}$$

$$(\vec{V} \cdot \vec{\nabla})\vec{V} = -\frac{1}{\rho}\vec{\nabla}P' + \nu\nabla^2\vec{V} \tag{6}$$

$\vec{V}$ is the velocity of the fluid, ρ is the density, and ν is the kinematic viscosity ($\nu=\mu/\rho$), P' is modified pressure, which is used when the lack of free surface effects

Equation (5) is a conservation equation, while equation (6) is a transport equation that represents the transport of linear momentum throughout the computational domain. Equation (4) is a scalar equation, while equation (6) is a vector equation. Both equations apply only to incompressible flows whose constants value ρ and ν. Thus, three-dimensional flow in Cartesian coordinates contains four coupled differential equations for four unknowns, u, v, w, and P' (equation 8-11). If the flow were compressible, Equation (8) and Equation (9) would need to be modified appropriately as Equation (10). Liquid flows can almost always be treated as incompressible, and for many gas flows, the gas is at a low enough Mach number that it behaves as a nearly incompressible fluid. For a working fluid with constant density(ρ) (i.e., incompressible flow), the rate of mass change with time (*t)*, in a control volume is balanced by the net mass flow. This is shown in the continuity equation, which is Equation (7).

$$\frac{\partial u}{\partial x}+\frac{\partial v}{\partial y}+\frac{\partial w}{\partial z}=0 \tag{7}$$

Where *u, v* and *w* are the x-, y- and z-directional velocity components at a specific position in the control volume, respectively.

A fluid element's momentum and concentration change rate in the control volume equals the sum of the forces acting on the element. For any 3D model, these forces comprise normal force stress and tangential force stress components in the x-, y- and z-directions, respectively. In fluid dynamics, the momentum and concentration change rate is expressed using the following Navier-Stokes equations.

$$\begin{aligned}\frac{\partial u}{\partial t}+u\frac{\partial u}{\partial x}+v\frac{\partial u}{\partial y}+w\frac{\partial u}{\partial z}\\ =-\frac{1}{\rho}\frac{\partial p}{\partial x}+\frac{\partial}{\partial x}\left(\frac{u}{\rho}\frac{\partial u}{\partial x}-u'u'\right)+\frac{\partial}{\partial y}\left(\frac{u}{\rho}\frac{\partial u}{\partial y}-u'v'\right)\\ +\frac{\partial}{\partial z}\left(\frac{u}{\rho}\frac{\partial u}{\partial z}-u'w'\right)\end{aligned} \tag{8}$$

$$\begin{aligned}\frac{\partial v}{\partial t}+u\frac{\partial v}{\partial x}+v\frac{\partial v}{\partial y}+w\frac{\partial v}{\partial z}\\ =-\frac{1}{\rho}\frac{\partial p}{\partial y}+\frac{\partial}{\partial x}\left(\frac{u}{\rho}\frac{\partial v}{\partial x}-v'u'\right)+\frac{\partial}{\partial y}\left(\frac{u}{\rho}\frac{\partial v}{\partial y}-v'v'\right)\\ +\frac{\partial}{\partial z}\left(\frac{u}{\rho}\frac{\partial v}{\partial z}-v'w'\right)\end{aligned} \tag{9}$$

$$\frac{\partial w}{\partial t}+u\frac{\partial w}{\partial x}+v\frac{\partial w}{\partial y}+w\frac{\partial w}{\partial z} \\ =-\frac{1}{\rho}\frac{\partial p}{\partial y}+\frac{\partial}{\partial x}\left(\frac{u}{\rho}\frac{\partial w}{\partial x}-w'u'\right)+\frac{\partial}{\partial y}\left(\frac{u}{\rho}\frac{\partial w}{\partial y}-w'v'\right) \\ +\frac{\partial}{\partial z}\left(\frac{u}{\rho}\frac{\partial w}{\partial z}-w'w'\right) \tag{10}$$

$$\frac{\partial C}{\partial t}+u\frac{\partial C}{\partial x}+v\frac{\partial C}{\partial y}+w\frac{\partial C}{\partial z} \\ =\frac{\partial}{\partial x}\left(D\frac{\partial C}{\partial x}-u'C'\right)+\frac{\partial}{\partial y}\left(D\frac{\partial C}{\partial y}-v'C'\right) \\ +\frac{\partial}{\partial z}\left(D\frac{\partial C}{\partial z}-w'C'\right) \tag{11}$$

Where μ is the dynamic viscosity of air; and*"uu,"uv,"uw,"vv,"vw and"ww are* the Reynolds stresses

In order to study the dispersion of aerosolized particulate matter influenced by air conditioning systems, we will use the Computational Fluid Dynamics (CFD) approach. The software used for CFD analysis in ANSYS FLUENT performs a three-dimensional (3D) numerical study of the indoors (Subhashini & Thirumaran, 2020). In assessing IAQ, air movement inside the built space is essential—velocity, relative humidity, temperature, and airflow pattern (Berville *et al.*, 2021). CFD is an alternative numerical method to study the impact of different variables on the IAQ, i.e., airflow pattern and velocity fields (Sun *et al.,* 2019; Kwon *et al.,* 2019). Many reviews concluded that CFD applications to indoor airflow simulation succeeded considerably (Deb *et al.*, 2022). The turbulent flow will be used in this study because the finer features of a turbulent airflow field are unsteady, and the three-dimensional areas are random, swirling, vortical structures suitable for simulated indoor air quality (IAQ) (Nandan *et al.*, 2020). The airflow pattern depends upon various factors such as air supply and exhaust, position and size of window or door, furniture arrangement in the room, and energy source availability. To simulate and predict the indoor airflow, numerical models will be made following the size of the building (Abid *et al.*, 2020). The advantages of CFD simulations are that they are more timesaving than experiments. Still, they need accurate thermal boundary conditions for airflow rate and direction, temperatures, and the RSP. This is important as the air entering the computational domain (inflow) or leaving the domain (outflow) is generally categorized with velocity-specified conditions or pressure-specific requirements (Yuan *et al.*, 2021). At the inlet, this study must determine the airflow velocity along the inlet face.

The temperature and turbulence properties of the incoming flow need to be specified (Pei & Rim, 2021). The airflow was simulated using the standard k–ε turbulence model known to produce accurate and experimentally validated results for indoor ventilation problems. Buoyancy was modelled using the Boussinesq approximation. Radiation was accounted for by activating the surface-to-surface (S2S) model, which calculates the energy exchange in an enclosure of grey-diffuse surfaces. The energy reflected from a surface is computed using its absolute temperature, emissivity, and reflectivity and the energy flux incident from its surroundings (Abid *et al.*, 2020). The radiation exchange between two surfaces depends on their size, separation distance, and orientation. These parameters are considered using view factors computed by the ANSYS FLUENT (Liu *et al.*, 2022). This is an essential step in the CFD process because it will define the generation of a grid representing the cells on which airflow variables are calculated throughout the computational domain. Modern commercial CFD codes come with grid generators and third-party grid generation programs generated in ANSYS FLUENT's grid package used in the simulation (Geng et al., 2023). The determination type of airflow and model used to run the simulation will produce a grid and simulation of the RSP flow inside the buildings.

In the room model, the principle of mass continuity is shown to be more applicable, which presents as the control volume. Therefore, the time interval of the change of mass in the room must be identical to the difference between the mass entering and exiting the room, as is evident in the following equation:

$$\partial\rho/\partial t + \nabla. (\rho \vec{v}) = 0 \qquad (12)$$

Considering ρ is the air density [kg / m^3] and v is the velocity vector [m / s].

The Navier-Stokes equations define the basic mathematics of the motion of fluids, as they mainly represent Newton's law (Law of Motion) applied to liquids. Based on Newton's second law of fluid flow, the momentum equation can be expressed in the following equation:

$$\nabla.(\rho\vec{v} \otimes \vec{v}) = \nabla.(\mu_{tot}\nabla \vec{v}) - \nabla p + \vec{F}_g + \vec{F}_{\Delta T} \quad (13)$$

Where μ_{tot} [kg / m. s] represents the total molecular and turbulent viscosity, p is the pressure [Pa], and $\vec{F}_g + \vec{F}_{\Delta T}$ contain parameters such as thermal differences, $\rho\vec{v} \otimes \vec{v} = \rho\vec{v}.\vec{v}^T$ is the outer product.

Equations 11 and 12 describe forces (body forces), while the left side describes time-dependent quantities such as acceleration.

The energy in the air is defined as the sum of thermal energy (internal and velocity components) and the gravitational potential energy in buoyancy-driven flows. Consequently, the energy can be maintained in a stable state as follows:

$$\nabla.(\vec{v}(\rho E + p)) = -\nabla.(\textstyle\sum_j h_j J_j) + S_h \quad (14)$$

J_j is the diffusion flux of species j, h_J is the enthalpy of species j, and S_h includes the heat or any other volumetric heat sources defined in the simulation process.

To numerically simulate the turbulent flow, it was modelled with the k-ε turbulence model. Depending on the flow's instantaneous velocity u (x, t) at position x and time t. The instantaneous velocity can be described at a specific location and time:

$$U_i = \overline{u_i} + u_1{'}_i \quad (15)$$

U_i can be described as an average of v for stable flow, and u'_i is fluctuation velocity. u'_i is obtained by measuring as the standard deviation of u'_i.

Turbulence intensity (TI) can be calculated as:

$$TI = \overline{u_i} / \overline{u_i} \times 100 \textit{ in percent} \quad (16)$$

The turbulent kinetic energy k is given per unit mass as:

$$k = 1/2\overline{u_i'^2} = 1/2\,(u_1'^2 + u_2'^2 + u_3'^2) \quad (17)$$

Computer simulations can contribute to obtaining higher accuracy of results, thus simplifying and improving the research process. The most crucial advantage of

CFDs is testing various system configurations (types of models, positions of equipment, etc.) virtually without creating real systems. In this way, numerical methods can optimize the suitable design of the ventilation system and adequate locations of air inlets/outlets to decrease the sources of infections in an operating room. The CFD model will be validated with the experimental dataset.

3.4.4 Source Apportionment Using Principal Component Analysis

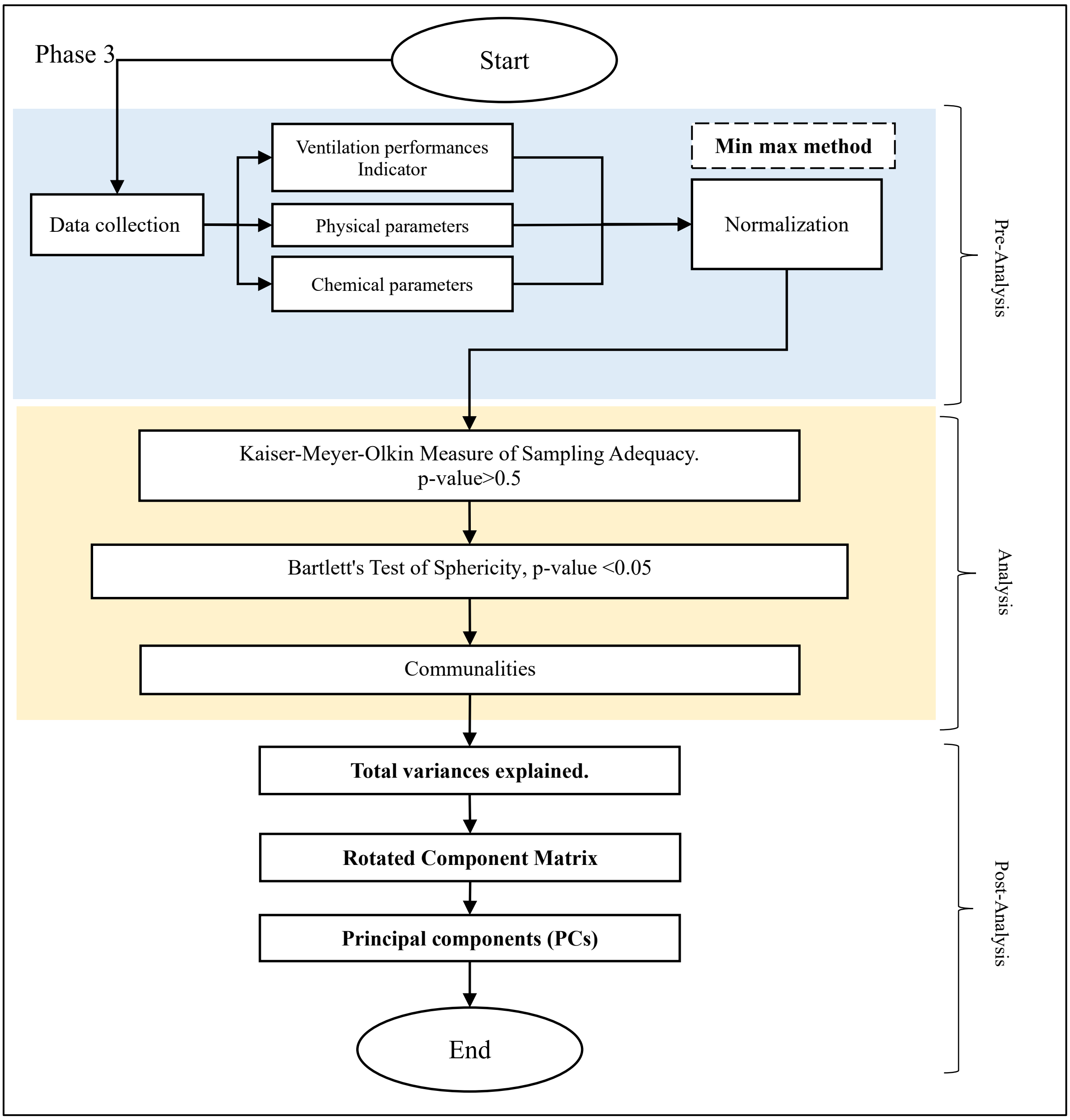

Figure 3.8 Flow chart Phase 3

The third phase flow chart is shown in Figure 3.8. Phase 3 consists of three stages: pre-analysis, analysis, and post-analysis. Pre-analysis involved data collection, which is stated in the section Data Acquisition and Pre-sampling, and this analysis only involved IAP that had been monitored during IAQ sampling at study areas with different monsoonal variations. Data collection consists of ventilation performance indicator (carbon dioxide, CO_2), chemical (total volatile organic compound, TVOC; formaldehyde (HCHO); carbon monoxide (CO); respirable suspended particulate (RSP)) and physical parameter (air movement, AM; temperature, (T); relative humidity (RH). Normalization was conducted using the min-max method or scaling. In developing models or analysis, the Min-Max scaling method is frequently employed to normalize the range of feature values to ensure they are within a specific interval, typically [0, 1] (Raju *et al.*,2020). This can be especially beneficial for enhancing the performance and convergence of numerous machine learning algorithms, as they may perform more efficiently or converge more quickly when the features are similar. By rescaling features to a fixed range, typically [0, 1] (Henderi *et al.*, 2021). Min-Max normalization converts them to a shared scale. The equation (18) shows the Min-max scaling in this normalization process.

$$X_{Norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \quad (18)$$

Where X is the original value, X_{min} is the minimum value of the feature in the dataset, X_{max} is the maximum value of the feature in the dataset, and X_{norm} is the normalized value.

Min-max scaling is employed to normalize features to a standard range, ensuring that each feature contributes equitably to the model. This is because min-max scaling can provide a uniform scale. This is crucial for algorithms sensitive to the magnitude of input features, such as gradient descent-based methods (e.g., linear regression, neural networks). In addition to optimization algorithms' enhanced convergence, the gradients will be more consistent, resulting in quicker convergence during training. Finally, preventing bias is crucial, as algorithms may become biased toward features with larger ranges if features have varying ranges. Normalization mitigates this risk by standardizing the input features.

PCA is a statistical analysis that is a quantifiable method that gives the result based on the correlation between variables and an uncorrelated set of data represented by the orthogonal conversion concept, which is interpreted as principal components (PCs) (Hasan & Abdulazeez, 2021). PCA is a proper mathematical method for reducing many data variables into a few more comprehensible factors, as shown in the PCA architecture model in Figure 3.9. This statistical approach reduces a set of intercorrelated variables into a few dimensions that gather a large amount of the variability of the original variables (Greenacre, 2022). In this study, PCA was used to obtain the sources of IAQ by quantifying the percentage of chemical and physical parameters. PCA can be expressed by Equation (19).

$$PC_i = l_{1\,i} X_i + l_{2i} X_2 + \ldots + l_{ni} X_n \quad (19)$$

Where PC_i is the *ith* principal component and X_i is the loading of the observed variable X_i

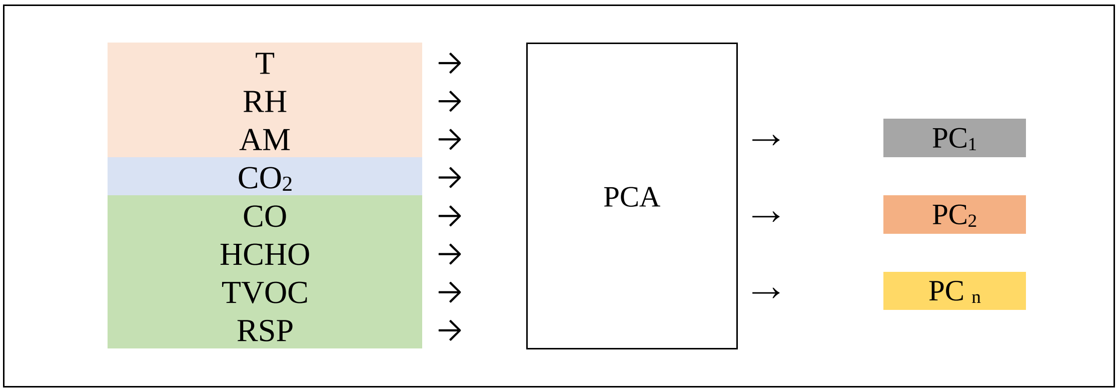

Figure 3.9 PCA architecture model

The quantification of potential sources was determined using the Principal Component Analysis (PCA) technique. Two requirements need to be fulfilled before proceeding with PCA. The two tests were Kaiser-Meyer Olkin (KMO) of Sampling Adequacy and Bartlett's Test of Sphericity. KMO needs to determine the acceptability of the data set, and the value must be more than 0.5 (Gewers *et al.*, 2021). The probability related to Bartlett's Test was also one of the requirements to be fulfilled before conducting PCA, in which the value must be less than 0.05 (<0.05) (Mahmoudi *et al.*, 2021). Then, the extraction values in the communalities table were checked. This is important as only the parameters contributing more than 50% of its variance in the data set were considered for further analysis. Otherwise, it was removed, and the KMO and Bartlett's tests were rechecked until all input parameters had more than 50% variance contribution in the data set (Beattie& Esmonde-White, 2021).

Later, the extraction values in communalities tables were examined. It is essential to determine that only parameters that contribute more than 50% in the variance contribution in the data set were considered for further analysis. Suppose the data set cannot fulfil 50% variances (Allee *et al.*, 2022). In that case, the data must be removed, and the KMO and Bartlett's test must be repeated until all the parameters have more than 50% variance contribution. Besides commonalities, eigenvalues also play important roles related to each linear component after rotation and extraction. The function of eigenvalues was to find the relation of each factor distinction, which was cleared up by particular linear components, besides demonstrating and explaining their eigenvalue in terms of variances percentage and the total initial eigenvalues must more than 1 (Muelle, 2022; Abdullah et al., 2019).

The principal components' capture of variance is denoted as the Total Variance Explained. Each principal component captures a portion of the dataset's total variance. Variance Explained by a Principal Component is the variance a specific principal component explains, typically expressed as a percentage of the total variance. Cumulative Variance Explained is the cumulative percentage of variance that can be accounted for by a specific number of principal components which more than 0.50 or 50% contributions which same goes with the selection of rotated principal components (Alias *et al.*, 2020). For instance, if the first two principal components collectively account for 85% of the total variance, these two PCs would preserve 85% of the original data's information. The Rotated Component Matrix is a factor analysis extension of PCA that simplifies the interpretation of the principal components (Arsad *et al.*, 2023). In order to facilitate the interpretation of the loadings (or weights), the component matrix undergoes rotation. Rotation does not alter the variance explained by the components; however, it facilitates the interpretation of the results (Almaiah *et al.*, 2022).

Principal Components (PCs) are the new axes or directions in the feature space that PCA identifies. Each principal component is a linear combination of the original features, and they are ordered such that the first principal component accounts for the maximum variance in the data, the second principal component accounts for the second most variance, and so on. The results for PCS can be divided into: PC1 Shows the first principal component is the direction along which the data varies the most; PC2, the second principal component, is orthogonal (uncorrelated) to the first and accounts for the next highest amount of variance; PC3 is the third principal component is orthogonal to both the first and second components and so forth, and the equation showed in equation (18)

3.5 Model development

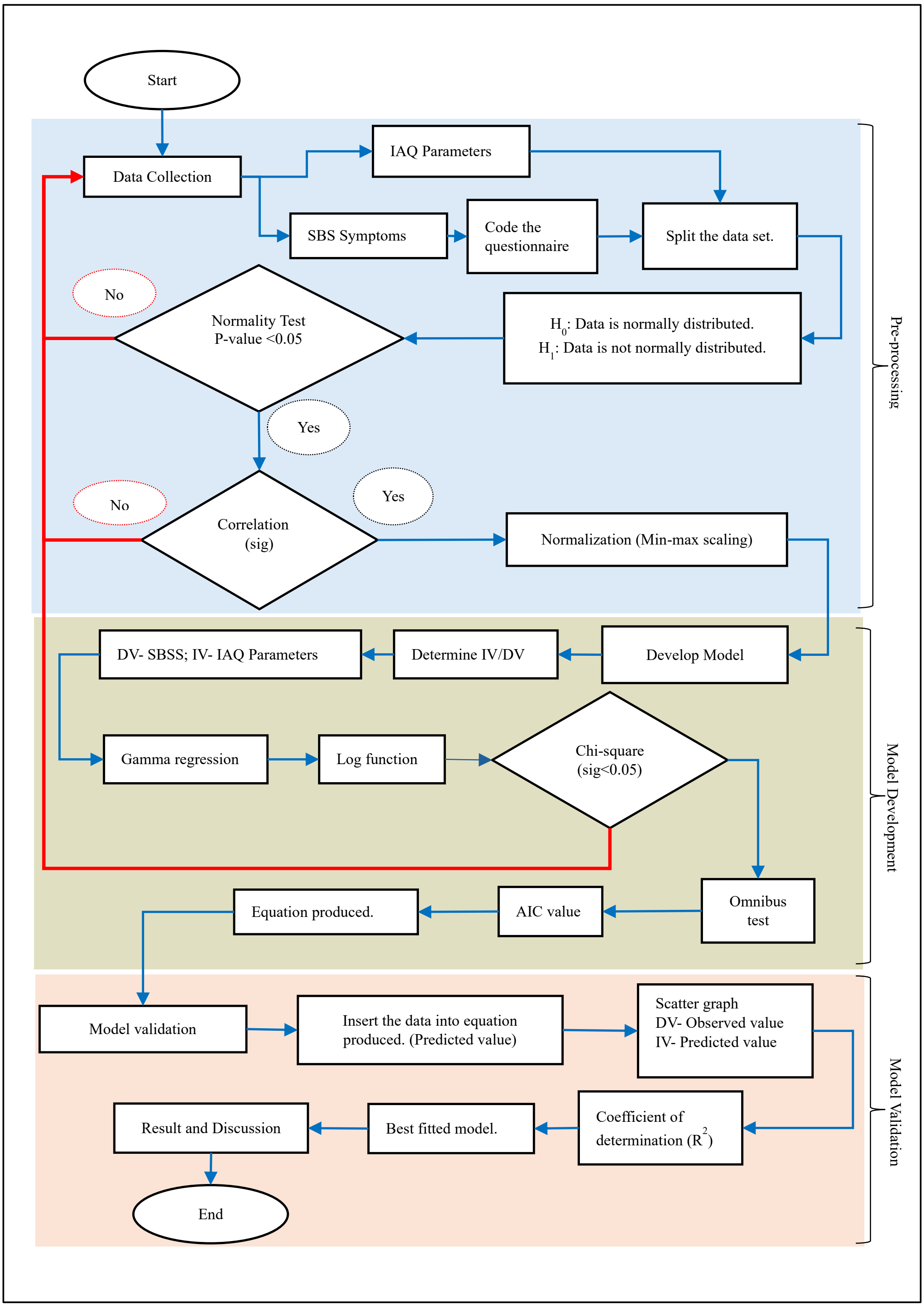

Figure 3.10 Flow chart Phase 4

Phase 4, shown in Figure 3.10, consists of three stages. The stages consist of pre-processing, model development, and model validation. Data collection was the same as section data acquisition and pre-sampling methods. The normalization used in this study was min-max scaling. The data was divided into two parts: a model data set (9-day sampling (day 1-9)) and a validation data set (last-day sampling data (day 10)).

This study used inferential statistics to analyze the normality of the data in a pre-processing stage. Assuming a 95% confidence level, if $p < 0.05$, the null hypothesis (H_o) is rejected, and it is concluded that the distribution is not normal (Rodriguez *et al*, 2020). The normality test was performed by applying the Kolmogorov-Smirnov method. Equation (20) showed that the hypothesis was defined to determine the normality of the data set and considered as an overview of the variation of air pollutant concentration. This result should be verified and investigated further using statistical analysis of inferential statistics widely used in air pollution studies, such as Analysis of Variance (ANOVA). ANOVA was conducted to determine whether a statistically significant difference exists in the air pollutant concentration among the stations. The one-way ANOVA was anticipated, in which air pollutants were compared with a single factor (Station).

H_o: *Data is normally distributed* (20)

H_1: *Data is not normally distributed*

The result was that the p-value was 0.000 ($p < 0.05$), which is significant. Therefore, it rejects H_o. Thus, it rejects H_o. Therefore, the data was not normally distributed, and the results were the same for SBSS. In various areas of empirical studies, researchers are often interested in testing the homogeneity of distributions across different samples. The normality test was performed by applying the Kolmogorov-Smirnov method (Anuar *et al.*, 2021). This test determined whether two distributions or an underlying probability distribution differed from a hypothesized distribution (Arulmozhi *et al.*, 2021). It is used when we have two samples from two populations that can be different. Thus, the data proved that it was not normally distributed.

The study proceeds with checking the second assumption of ANOVA. The hypothesis was defined to test co-variance in the data set.

H_O: *Data has equal variance* (21)

H_1: *Data has no equal variances*

The co-variance was conducted by applying Levene's Test. If the results revealed that the p-value was 0.000 (<0.005), it showed significance. Therefore, H_o is rejected for physical, chemical, and performance indicators. Both normality and co-variance tests revealed that this dataset fails to meet parametric characteristics. Nonparametric tests are needed to determine the statistically significant difference between air pollutants and sick building syndrome symptoms (SBSS). Kruskal Wallis test was often used for the non-parametric test (Rodriguez, 2020; Ruxton & Beauchamp, 2008). Kruskal–Wallis test is a non-parametric statistical test that evaluates whether two or more samples are drawn from the same distribution (Guo *et al.*, 2013). Like ANOVA, the Kruskal-Wallis test compares two or more samples, focusing on cases with three or more samples. The H_o of the Kruskal Wallis was different from those of ANOVA. For ANOVA, the H_o was all the means of the populations from which the samples are drawn are the same; the alternative hypothesis (H_1) implies that at least two of these means differ. For the Kruskal Wallis, the null H_0 is stochastic homogeneity, with stochastic heterogeneity being the H_1 (Vieira *et al.*, 2019). The hypothesis was defined as in equation (22).

H_o: $\mu s1 = \mu s2 = \mu s3 = \mu s4$ *(no mean difference for the 4 sites)* (22)

$H1$: $\mu s1 \neq \mu s2 \neq \mu s3 \neq \mu s4$

Kruskal Wallis Test displayed a p-value with a statistically significant difference when the value was less than 0.005 (p<0.05) (Sherwani *et al.*, 2021). Thus, H_o is rejected. This value showed that air pollutant concentration has a statistically significant difference. Further analysis was performed to compare air pollutant concentrations between each site simultaneously.

After determining the data set types, the pre-processing analysis proceeds with normalization. Min-max or scaling was employed to perform normalization (Ahmed & Jena, 2023). The Min-Max scaling method is frequently implemented in developing models or analyses to ensure that the range of feature values is within a specific interval, typically [0, 1]. This can be particularly advantageous for improving the performance and convergence of various machine learning algorithms, as they may perform more efficiently or converge more rapidly when the features are of comparable size (Wolkoff *et al.*, 2018). Min-max normalization typically converts features to a shared scale by scaling them to a fixed range [0, 1]. The Min-max scaling in this normalization procedure is illustrated in equation (17).

A GLM is frequently employed to estimate the associations between interior air quality and occupants (Mentese *et al.*, 2020). Consequently, the GLM was implemented to identify correlations between the occupants' SBS symptoms and the IAQ measurement data in this investigation. The GLM combines linear and non-linear models that employ a distribution of exponential functions and logistic models. The GLM comprises three subsequent components (Wolkoff *et al.*, 2021).

- Random components: n values of the response variable (y_i, …...y_n)
- Systematic component: a linear structure for the regression model ($\eta = \beta x^T$), where $x^T = (1, x_{i1}, x_{i2}, \ldots, x_{in})^T$, *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 (23):

$$g(\mu_I) = x_i^t \beta, i = 1 \ldots\ldots K \tag{23}$$

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:

$$g(\mu_i) = \mu_i \tag{24}$$

Then

$$\mu_i = E(Y_i) = x_i^t \beta \tag{25}$$

The resulting model is the linear regression model. Alternatively, consider the function g as a logarithmic function, and Yi has a Gamma distribution. In that case, the model will result in a Gamma regression model, and each term β_i is the effect of variable X_i in $g\ (\mu_i)$ (Licina & Yildirim, 2021). Each β_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 consist of physical and chemical parameters (Mentese *et al.*, 2020). Statistical Package software for Social Sciences SPSS 10.0 for Windows was used to build and analyse the model.

Each distribution has a unique link function. The distribution most used on the estimation of air pollution health impacts in Gamma function (Belotti *et al.*, 2020; Soleimani *et al.*, 2019), of which link function is $\eta = \log(\mu)$,then $\mu = e^{i}$. Thus, η follows a linear model's assumptions rather than μ, using matrix notation

Gamma

$$\log(\mu) = \beta x^T + f \tag{26}$$

β_j is the vector of the coefficients to be estimated (co-variables) and $f(x_j)$ are the smoothing functions for the confounding variables (temperature and humidity) and long-term seasonality present in the data. β_0 corresponds to the intercept of the curve associated with the vector of unitary values. Where $Y = y_1, \dots, y_n$is the function f evaluated at time $t=1,..n$ and x^T is the $n \times m + 1$ design matrix containing a column of ones and the other explanatory times series variables $x_i, \dots x_m$. Given an $m \times d$ splines basis matrix B, we can rewrite equation (27) as

$$\log(\mu) = \beta x^T + \beta\gamma \tag{27}$$

The chi-square test assesses the model's goodness of fit in the context of GLMs. Some applications include the deviance test, which compares the model's fit to a saturated model (one with a perfect fit) or a simpler model. The test statistic equation (28).

$$\text{Deviances} = 2\,[\log(\mathit{Likelihood\ of\ the\ fitted\ model}) - \log(\mathit{Likelihood\ of\ saturated\ model})] \tag{28}$$

This statistic approximates a chi-square distribution with degrees of freedom equal to the difference in the number of parameters between the two models under the null hypothesis (that the simpler model is accurate). The Goodness-of-Fit test can also be employed to evaluate the model's overall fit compared to the null hypothesis of no effect. The Omnibus test assesses the model's overall significance, particularly in GLMs. It determines whether at least one of the predictors in the model has a non-zero coefficient. It frequently employs the chi-square distribution to ascertain the significance of the overall model fit. It entails comparing the complete model (which includes all predictors) and a null model (which contains no predictors). The test proceeds with the AIC Value (Akaike Information Criterion) as shown in equation (29). The AIC is employed to compare and select models. In order to prevent overfitting, the AIC penalizes models with an increased number of parameters. The model with the lowest AIC is regarded as superior in the comparison.

$$AIC = 2\log(Likelihood) + 2k \tag{29}$$

Likelihood is the likelihood of the model given the data; it measures how well the model fits the data, and k is the number of estimated parameters.

Lower AIC values indicate a superior model fit relative to complexity. Lower values also indicate a model that balances simplicity and fit (Kasali & Adeyemi, 2022). AIC values are employed to compare various models fitted to the same dataset. The model with the lowest AIC is the favored option. In GLMs, including Gamma regression models, AIC is used to evaluate and compare the models and use the likelihood function for a GLM; the likelihood function represents the probability of the observed data given the model parameters (Li *et al.*, 2022).

Model validation is a critical procedure for assessing and ensuring the reliability and accuracy of a statistical or machine-learning model. This process entails systematically assessing the model's ability to generalize to new, unobserved, validated data and confirming that it generates reliable results. This encompasses the utilization of test data. Validate the model by employing a distinct dataset not utilized during the model's training (Less *et al.*, 2019). This facilitates the evaluation of the model's generalizability. Cross-validation entails partitioning the data into subsets, training the model on specific subsets, and validating the model on others. The coefficient of determination, frequently referred to as R^2, is a critical metric utilized in model validation to assess the efficacy of regression models. It quantifies the extent to which the independent variables predict the variance of the dependent variable. The coefficient of determination R^2 quantifies how well the model's predictions approximate the data point and the equation shown in Equation (30), and a higher R^2 value indicates a better fit of the model to the data. This R^2 evaluates how well the model performs on new (out-of-sample) data, specifically comparing forecasted values to actual observed values. This is common in time series forecasting or predictive models applied to unseen data. R^2 as a performance indicator measures how well the model fits the existing data (training or testing) while R^2 for forecasted vs. observed measures the model's predictive performance on unseen data and a discrepancy between the two often indicates overfitting or that the model struggles with future uncertainty (Garg *et al.*, 2022 ; Cerqueira *et al.*, 2019).

$$R^2 = 1 - \frac{\sum_{i=1}^{n}(y_i - \hat{y})^2}{\sum_{i=1}^{n}(y_i - \bar{y})^2} \tag{30}$$

Where:

y_i actual observed values (new data).

$\hat{y}$ forecasted or predicted values for new data.

$\bar{y}$ mean of the observed values y_i in the forecast period.

3.6 Model validation

A performance indicator (PI) was used to determine the model's suitability for predicting the future. There are two categories of performance indicators: error measurement and accurate measurement. There are three performance indicators used to measure the error in this study: normalized absolute error (NAE), root mean square error (RMSE) and mean absolute error (MAE). Two performance indicators used in this study to measure the model's accuracy are the index of agreement (IA) and coefficient of determination (R^2), as shown in Table 3.3.

Table 3.3 Performances Indicator (Abdullah *et al*., 2019)

Indicator	**Equations**	
Normalized Absolute Error (NAE)	$NAE = \frac{\sum_{i=1}^{n}\lvert P_i - O_i\rvert}{\sum_{i=1}^{n} O_i}$	A value closer to zero is better.
Root Mean Square Error (RMSE)	$RMSE = \frac{1}{n-1}\sum_{i=1}^{n}(P_i - O_i)^2$	A value closer to zero is better.
Mean Absolute Error (MAE)	$MAE = \frac{\sum_{i=1}^{n}\lvert P_i - O_i\rvert}{n}$	A value closer to zero is better.
Index of Agreement (IA)	$IA = 1 - \left\lvert\frac{\sum_{i=1}^{n}(P_i - O_i)^2}{\sum_{i=1}^{n}\lvert P_i - \bar{O}\rvert + \lvert O_i - \bar{O}\rvert^2}\right\rvert$	Value closer to one is better.
Coefficient of determination (R^2)	$R^2 = \left(\frac{\sum_{i=1}^{n}(P_i - \bar{P})(O_i - \bar{O})}{n.S_{pred}.S_{obs}}\right)^2$	Value closer to one is better.

Where n is a total number measurement, P_i is a forecasted value, O_i and is an observed value, $\bar{P}$ is mean forecasted value,$\bar{O_i}$ is mean observed value, S_{pred} is the standard deviation of forecasted value and S_{obs} is the standard deviation of the observed value.

CHAPTER 4

RESULTS AND DISCUSSION

4.1 Results

This section shows the results of each objective in completing this chapter. Section 4.1.1 showed demographic and SBS symptoms and IAP compliance with the standard. Section 4.1.2 shows the simulation of computational fluid dynamics for all study areas, while Section 4.1.3 presents the PCA result. Lastly, a GLM at Section 4.1.4 using a gamma model was developed and validated for each study area with different monsoonal seasons at different sub dominant economy.

4.1.1 Demographic, Sick Building Syndrome (SBS) symptoms and Compliances of the Indoor Air Quality (IAQ)

The questionnaire was distributed among respondents in the study areas. This is important to determine the point of view of occupants or workers inside the buildings. Demographic factors showed the age, gender and department of each respondent or worker in each study area. Figure 4.1 shows the percentage of age range for all study areas, and Table 4.1 shows results for gender percentages in each study area. The percentage of each occupant's departments or division in each study area is shown in Figure 4.2. In Figure 4.1, Sekolah Kebangsaan Tanjung Gelam (S1) showed that 54.5% (N=6) of the age respondents aged less than 25 years old, 9.1% (N=1) from23-39 years old, 27.3% (N=3) for 40-55 years old and 9.1% (N=1) for more than 55 years old. The number of teachers in the teachers' room at Sekolah Kebangsaan Tanjung Gelam was 11, which consisted of 5(45.5%) males and six females (54.5%), as shown in Table 4.1.

Figure 4.2 shows the results percentage of each occupant's departments or division in each study area, which consists of mathematics, English, Islamic education, sciences and Malay language division for each teacher at Sekolah Kebangsaan Tanjung Gelam (S1).

There were 33 workers who contributed to answering the questionnaire at TMG Mart (S2). According to the study, 39.4% of the workers were male, and the rest, 60.6%, were female, as shown in Table 4.1. Workers in TMG Mart consist of four stages of age range consists of less than 25 years old (21.2%, N=7), 25 to 39 years old (54.5%, N=18), 40 to 55 years old (21.3%, N=7), and more than 55 years old (3%, N=1) as shown in Figure 4.1. TMG Mart (S2) workers were divided into three divisions: admin or clerk, cashier, and sales assistant. The administrative or clerk position consists of 3 workers (9.10%), the cashier position is ten workers (30.3%), and the sales assistant position is 20 workers (60.6%), which involves answering questionnaires related to SBSS. Administrative or clerical roles in a supermarket involve a diverse range of tasks that support the operational efficiency of the store. These roles are critical for ensuring smooth daily operations, effective customer service, accurate record-keeping, and overall organisational success. The subsequent division in TMG Mart was a sales assistant, responsible for delivering excellent customer service, managing product displays, handling transactions, and maintaining store operations. This role requires strong communication skills, attention to detail, and the ability to work effectively as part of a team to create a positive customer shopping experience.

Next, demographic factors were evaluated in Mset Inflatable Composite Corporation Sdn. Bhd. (S3), which involved 16 workers, and all workers were male. Figure 4.1 showed that 68.8% (N=11) of workers aged 25-39 years old and 31.2% (N=5) of workers ranged from 40-55 years old. Workers at S3 include fiberglass, blacksmiths, electricians, technology executives, and boat makers division or specialty. 31.30% (N=5) of the workers were in the glass division which consists of resin applications, curing, and hardening, which allows the resin and fiberglass to cure appropriately by controlling the temperature and humidity to ensure that fiberglass sets appropriately and achieves the desired strength. Boat maker specialists or divisions are involved in sanding and fairing the surfaces to prepare them for painting or coating, besides painting and coating by applying protective and decorative finishes such as primer, paint, and gel coats. The boat-maker workers who contributed to answering the questionnaires were six workers, which is 37.50% of the total workers who are working in the study area, as shown in Figure 4.2 c). Two workers specialised in blacksmithing, which involved procuring and preparing raw metal materials, cutting and shaping them, and hammering and shaping them. Wielding and soldering to ensure robust and clean welding to maintain structural integrity was a job scope for blacksmiths. Two out of sixteen respondents or workers in S3 were electricians, and one was a technician executive. Their function was to install electrical wiring throughout the boat, including power cables, control wires, and communications lines, besides ensuring all wiring was routed properly and safely.

The fourth study area represents hospitality subsectors: Raia Hotel & Convention Centre Terengganu (S4). Ten out of eighteen workers answering the questionnaire come from the administrative department located in the lobby and public office of S4, and the remaining 8 (44.4%) workers come from the food and beverages (F &B) department. Table 4.1 showed that 55.6% (N=10) of the workers were male, and the rest were female. All workers who contributed to answering the questionnaire ranged between less than 25 years old (38.9%, N=7), 25-39 years old (44.4%, N=8), and 40-55 years old (16.7%, N=3), as shown in Figure 4.1. 55.66% of the workers involved in this study were male, and the rest were female. The worker division is divided into admin, assistant manager food and beverages (F&B), manager F&B, bell boy, coffee maker, and front desk. The admin involved administrative support such as office management, such as managing supplies, equipment, and paperwork, as well as document handling and coordinating staff schedules by ensuring adequate coverage for different shifts and departments and managing time-off requests and attendance tracking. 33.3% (N=6) of the respondents who answered the SBSS questionnaire come from the admin division. The subsequent division is assistant manager F&B (1 worker, 5.6%), coffee maker (1 worker, 5.6%), manager F&B (1 worker, 5.6%), and waitress (5 workers, 27.80%). All of these workers are part of the F&B department. The food and beverage department in a hotel encompasses a wide range of responsibilities aimed at providing exceptional dining experiences, managing operational efficiency, and ensuring high standards of quality and service. This role requires a combination of management skills, financial acumen, and a passion for hospitality to create memorable experiences for guests while driving the success of the hotel's F&B offerings. Administrative departments consist of admin (33%, N=6), bell boy 11.10%, N=2), and front desk (11.10%, N=2). The administrative department of a hotel is accountable for a diverse array of responsibilities that contribute to the hotel's overall operations. This encompasses the coordination of other departments, the management of visitor services, the management of financial transactions, and the assurance of regulatory compliance. This position requires effective communication, meticulous attention to detail, and strong organisational abilities.

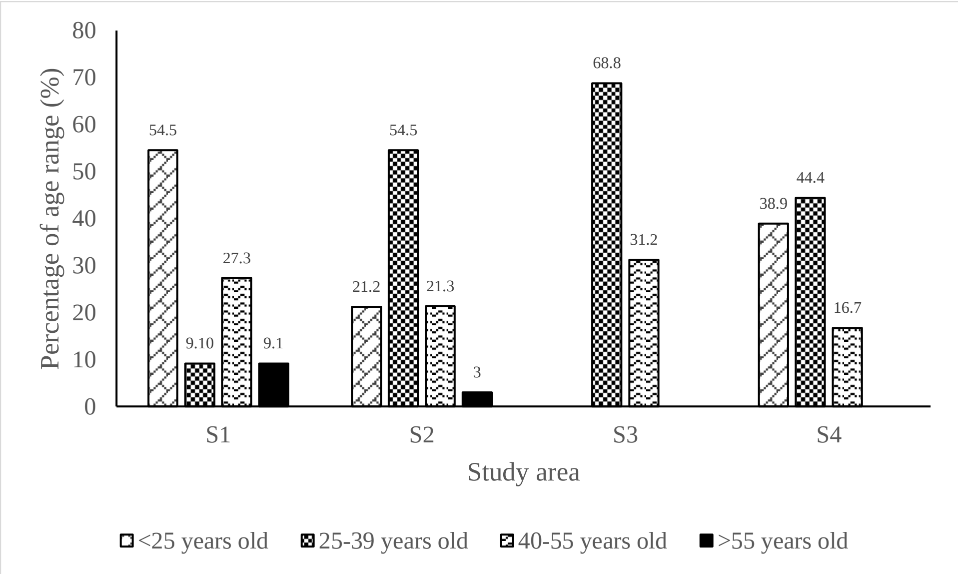

Figure 4.1 Percentage of age range in the study area

Table 4.1 Percentage gender of respondents in the study area

Gender	S1 (N)	S2 (N)	S3 (N)	S4 (N)
Male	45.5 (5)	39.4 (13)	100 (16)	55.6 (10)
Female	54.5 (6)	60.6 (20)		44.4 (8)

N=number of occupants

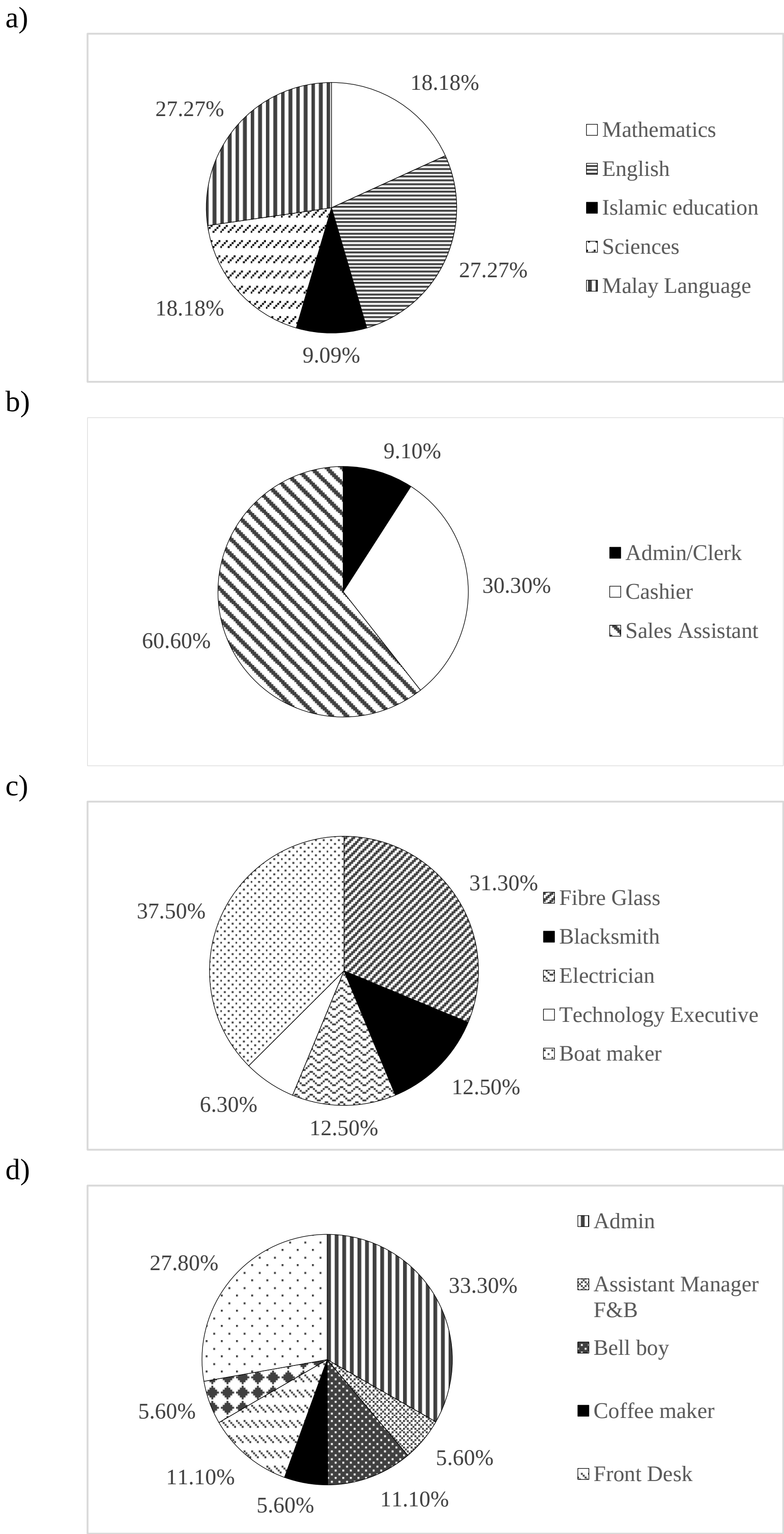

Figure 4.2 a) Percentage of each occupant's departments in S1; b) Percentage of each occupant's departments in S2; c) Percentage of each occupant's departments in S3; d) Percentage of each occupant's departments in S4.

The SBS symptoms questionnaire consists of past 3-month symptoms. The symptoms that been stated in the questionnaire were draught, room temperature too high, varying room temperature, room temperature too low, stuffy bad air, dry air, unpleasant odour, passive smoking, dust and dirt, as shown in Table 4.2 for Southwest Monsoon (SWM) and Northeast Monsoon (NEM). The first question for these sections was a draught, in which occupants agreed that their workplace faced draught, with 27.3% (S1), 60.6% (S2),12.5 (S3) and 5.6% (S4) answering "Yes, often (every week)" during SWM and 36.4% (S1), 54.5% (S2), 25% (S3) and 16.7% (S4) for NEM. The remainder of the workers or occupants answered "Yes, sometimes" with45.5% (S1), 30.3% (S2), 87.5% (S3), 88.9% (S4) for SWM and 36.4%(S1), 24.2% (S2), 75%, 66.7% (S4) for NEM. Most of the workers in the study areas agreed that they faced draught, but some workers believe that they did not face draught situation because the workers answered "No, never" with 27.3% (S1), 9.1% (S2), 5.6% (S3) during SWM and 27.3% (S1), 21.2% (S2), 16.7% (S4) for NEM.

The other item asked in the questionnaire was whether the room temperature was too high. Most of the workers believe that they face high room temperatures sometimes, with 45.5% (S1), 33.3% (S2), 68.8% (S3), 44.4% (S4) for SWM and 45.5% (S1), 33.3% (S2), 81.25% (S3), 44.4% (S4) for NEM which agreed with the answer "Yes, sometimes". 18.2% (S1), 54.5% (S2), 25% (S3), 27.8% (S4) during SWM and 27.3% (S1), 48.5% (S2), 18.75% (S3), 33.3% (S4) during NEM which the workers were agreed that their room temperature too high with the answer "Yes, often (every week)". Reminder workers agreed that their workplace temperature is not too high with the answer "No, never". 36.4% (S1), 12.1% (S2), 63% (S3) and 2.8% (S4) of the workers agreed that their workplace temperature was not too high during SWM and 27.3% (S1), 18.2% (S2), 22.2% (S4) for NEM.

Varying room temperature was one of the items questioned in the SBS symptoms questionnaire. The workers agreed that they did not face varying room temperatures, with 18.2% (SWM) and 9.1% (NEM) at S1, 3% (SWM) and 9.1% (NEM) for S2, 25% (SWM) and 12.5% (NEM) for S3, 38.9% (SWM) and 27.8% (NEM) for S4 with "No, never" answered. Table 4.2 also shows that the workers also feel varying room temperatures with the answer "Yes, often (every week)" and "Yes, sometimes".

Most of the workers decided the room was varying with 72.7% (NEM) for S1, 66.7 (SWM) and 60.6% for S2, 37.7% (SWM) and 25% (NEM) for S3, 33.3% for S4 with the answer “Yes, sometimes”.

SBS symptoms questionnaire also asked about stuffy “bad air”. Workers at S1, S2, S3, and S4 agreed that their workplaces occasionally have varying levels of foul air, with 90.9%, 63.6%, 75%, and 61.1% of workers responding "Yes, sometimes" during SWM. The labourers also experience a sense of stuffiness and poor air quality during NEM, with 81.8%, 51.5%, 62.5%, and 61.1% of respondents at S1, S2, S3, and S4 responding "Yes, sometimes". Meanwhile, 3% (SWM), 6.1% (NEM), 12.5% (SWM), 25% (NEM), and 33.3% (SWM), 22.2% (NEM) for S2, S3 and S4 of the respondents answered "No, never" in response to the absence of stuffy, poor air in the workplace.

Most employees concur that their workplace is dry air, with responses of "Yes, often" and "Yes, sometimes". Conversely, a small number of employees indicate that their workplace is comfortable, with responses of "No, never." The employees were exposed to dry air in the following proportions: 27.3% (SWM), 36.4% (NEM) for S1, 51.5% (SWM), 48.5% (NEM) for S2, 25% (SWM), 12.5% (NEM) for S3, and 44.4% (SWM), 61.1% (NEM) for S4 with workers responded, "Yes, sometimes". The percentage of employees who disagreed that the workplace had dry air was 27.3% for SWM and NEM for S1, 9.1% for SWM and NEM for S2, 38.90% (SWM), 33.3% (NEM) for S4, and only S3 did not have workers who disagreed with the presence of dry air, with responses of "No, never."

The response "Yes, sometimes" was given in response to an unpleasant odour. For S1, the percentage of employees who encountered disagreeable odours was 36.4% for NEM and SWM, 69.7% for NEM and SWM, 63.6% for SWM and S2, 68.8% for SWM and SWM, 87.5% for S3, and 55.6% for SWM and NEM and S4 with the response "Yes, sometimes". The workers who denied that they encountered unpleasant odours responded, "No, never." The percentage of employees who responded "No, never" was 45.5% for S1 SWM and NEM, 6.1% (SWM), 12.1% (NEM) for S2, and 38.9% for S4 in both monsoonal variations.

"No, never" is the response of the majority of the occupants who do not engage in passive smoking. The percentage of individuals who did not engage in passive smoking was 90.9% for both monsoonal variations at S1, 33.3% for both monsoonal variations at S2, 33.3% (SWM) and 16.7% (NEM) for S4. In addition, the workers were passively smoking, as indicated by the response "Yes, often". S2 and S3 showed that the 24.2% and 93.75% percentages during SWM and NEM consisted of 38.9% and 22.2% during NEM at S4.

The questionnaire included indicators such as dirt and dust. Majority of employees concur that they encountered dust and debris at their place of employment, except S4, which responded with "Yes, often" and "Yes, sometimes." At S1, 81.8% of workers contribute in both monsoons, 75.8% of workers participate in NEM and SWM at S2, 12.5% of workers participate in SWM, and 6.25% of workers participate in NEM at S3 and the percentage of respondents who responded "Yes, sometimes" was 16.7% in SWM and 27.8% in NEM at S4. S1 and S2 showed that 18.2% and 15.2% of workers participated in SWM and NEM, respectively. The percentages for SWM and NEM are 87.5% and 93.75%, respectively, as illustrated in Table 4.2 for S2. The percentage of S4 respondents who answered "Yes, often" was 5.6% for SWM and 16.7% for NEM.

Table 4.2 Percentage of past 3-month symptoms among workers in each study area

Past 3-month symptoms								
	S1		S2		S3		S4	
	SWM	NEM	SWM	NEM	SWM	NEM	SWM	NEM
Draught								
Yes, often (every week)	27.3	36.4	60.6	54.5	12.5	25	5.6	16.7
Yes, sometimes	45.5	36.4	30.3	24.2	87.5	75	88.9	66.7
No, never	27.3	27.3	9.1	21.2	-	-	5.6	16.7
Room temperature too high								
Yes, often (every week)	18.2	27.3	54.5	48.5	25	18.75	27.8	33.3
Yes, sometimes	45.5	45.5	33.3	33.3	68.8	81.25	44.4	44.4
No, never	36.4	27.3	12.1	18.2	6.3	-	27.8	22.2
Varying room temperature								
Yes, often (every week)	18.2	18.2	15.2	12.1	37.5	43.75	5.6	16.7
Yes, sometimes	63.6	72.7	81.8	78.8	37.5	43.75	55.6	55.6
No, never	18.2	9.1	3	9.1	25	12.5	38.9	27.8
Room temperature too low								
Yes, often	72.7	-	9.1	3	-	-	66.7	50
Yes, sometimes		72.7	66.7	60.6	37.5	25	33.3	
No, never	27.3	27.3	24.2	36.4	62.5	75	-	50

Stuffy bad air								
Yes, often	9.1	18.2	33.3	42.4	12.5	12.5	5.6	16.7
Yes, sometimes	90.9	81.8	63.6	51.5	75	62.5	61.1	61.1
No, never			3	6.1	12.5	25	33.3	22.2
Dry air								
Yes, often (every week)	45.5	36.4	39.4	42.4	37.5	43.75	16.7	5.6
Yes, sometimes	27.3	36.4	51.5	48.5	25	12.5	44.4	61.1
No, never	27.3	27.3	9.1	9.1			38.9	33.3
Unpleasant odour								
Yes, often (every week)	18.2	18.2	24.2	24.2	31.3	12.5	5.6	5.6
Yes, sometimes	36.4	36.4	69.7	63.6	68.8	87.5	55.6	55.6
No, never	45.5	45.5	6.1	12.1			38.9	38.9
Passive smoking								
Yes, often (every week)			24.2	24.2	93.75	93.75	38.9	22.2
Yes, sometimes	9.1	9.1	42.4	42.4	6.25	6.25	27.8	61.1
No, never	90.9	90.9	33.3	33.3			33.3	16.7
Dust and dirt								
Yes, often	18.2	18.2	15.2	15.2	87.5	93.75	5.6	16.7
Yes, sometimes	81.8	81.8	75.8	75.8	12.5	6.25	16.7	27.8
No, never			9.1	9.1			77.8	55.6

Table 4.3 shows the workers' answers to the present symptoms. The first present symptom that has been evaluated is a headache. Most workers faced headaches with the answer “Yes, sometimes,” with percentages of 72.7 %, 33.4%, and 66.7% for both monsoonal seasons for S1, S2, and S4. S3 shows that 68.8%(SWM) and 87.5% (NEM) with the answer “Yes, sometimes” from the workers. Even though most of the workers agreed that they suffered a headache for the present symptoms, there were also a few workers who disagreed that faced headaches with the answer “No, never,” with percentages of 18.2% for S1 and 42.4% for S2 at both monsoonal seasons, besides 18.8% (SWM), 27.8% (NEM) for S3 and 27.8% (SWM), 22.2% for S4.

The second symptom was feeling heavy-headed; almost all the workers agreed that they faced those symptoms with the answers “Yes, often” and “Yes, sometimes.” Most workers agreed they faced heavy headedness with the answer “Yes, sometimes,” with 45.5% for S1 during SWM and NEM and 36.4% for both monsoonal seasons at S2. 43.8% (SWM), 25% (NEM) was the percentage of workers that agreed that they faced feeling heavy-headed at S3 and 55.6% (SWM),50% (NEM) at S4. Some workers disagreed that they felt heavy-headed by answering “No, never,” with 27.3% and 42.4% for S1 and S2 for both monsoonal seasons, SWM and NEM. 56.3% (SWM), 68.75%

(NEM) for S3, and 33.3% (SWM), 22.2% (NEM) for S4 disagreed that they felt heavy-headed with the answer "No, never."

Next is fatigue and lethargy, which most workers agreed they felt for the present symptoms. During SWM, 63.6%, 48.5%, 75%, and 66.7% of the workers at S1, S2, S3, and S4 agreed that they felt fatigued and lethargy with the answers "Yes, sometimes," while 63.6% (S1), 48.5% (S2), 93.75% (S3) and 50% (S4) for NEM. A few workers disagree that they faced fatigue and lethargy, with 18.2%,27.3%, 12.5%, and 11.1% for S1, S2, S3, and S4 during SWM and 18.2%, 27.3%, 11.1% for S1, S2 and S4 during NEM with the answer "No, never."

Drowsiness is one of the present symptoms evaluated. A few of the workers disagree that they faced it for the present symptoms with the answer, "No, never.".27.3%, 6.1%, 37.5% and11.1% were answered from workers during SWM with the answer "No never" for S1, S2, S3, and S4. 27.3%, 12.1%,54.25% and 61.1% for S1, S2, S3 and S4 for NEM. Most workers felt drowsiness with the answer "Yes, often" and "Yes, sometimes." 63.6% and 9.1% of the workers answered, "Yes sometimes" and "Yes, often" for S1; the same goes with S2 workers which answered "yes, sometimes" with 66.7% during SWM, 63.6% for NEM and "Yes, often" with 27.3% (SWM) and 24.2% (NEM) at S2.

The fifth symptom was dizziness, of which 72.7% and 51.5% of the workers at S1 and S2 during SWM and NEM agreed that they felt dizziness by the answer "Yes, sometimes." 62.5% and 77.8% of the workers at S3 and S4 also agreed that they feel dizziness for present symptoms for SWM and 75% (S3), 27.8% (S4) for NEM. A few workers agree that they felt dizziness, which is frequently by answering "Yes, often," with 18.2% for both area SWM and NEM at S2 and 6.25% during NEM at S3. Even though most of the workers agree that they faced dizziness, there are a few workers that disagree with 27.3% during SWM and NEM at S1, 30.3% during SWM and NEM at S2, 37.5% (SWM), 18.75%(NEM) for S3 and 22.2% (SWM), 72.2% (NEM) for S4 that answer "No, never."

Nausea or vomiting is one of the present symptoms, and most workers disagree that they feel it. 72.7% for both monsoonal seasons at S1, 84.8% at both monsoonal seasons for S2, 56.3% (SWM), 75%(NEM) for S3, and 55.6% (SWM), 61.1% (NEM) for S4 answered “No, never” towards nausea or vomiting symptoms. A few of the workers agreed that they felt nausea or vomiting by answering “Yes, sometimes” and “Yes, often”. “Yes, often” answers consist of 9.1% for SWM and NEM in S1, 6.25% for NEM at S3, and the rest 18.2% of workers during SWM and NEM at S1, 15.2% during SWM and NEM at S2, 43.8% (SWM),18.75%(NEM) for S3 and 44.4% (SWM), 38.9% (NEM) at S4 answer “Yes, sometimes”.

Workers agreed that they cough, with a majority of them answering, “Yes, sometimes.”. 63.6% of workers at S1 at both monsoons, 54.5% (SWM),45.5% (NEM) for S2, 62.5% (SWM), 18.75% (NEM) for S3 and11.1% and 55.6% for S4 of the workers answer “Yes, sometimes.” There also workers that answered that they frequently felt cough with the answer “Yes, often,” with 18.2% for both monsoonal areas at S1, 15.2% (SWM), 6.1% (NEM) at S2, 12.5% during NEM at S3 with the answer “Yes, often”. “No, never” was answered by workers who had never felt a cough during the present time. There were18.2% for NEM and SWM at S1, 30.3% (SWM), 48.5% (NEM) for S2, 37.5% (SWM), 68.75% (NEM) for S3, and 88.9% (SWM), 44.4% (NEM) for S4 that agreed that they never felt cough for the present time.

Next is an irritated, stuffy nose, which most of the workers in all study areas agreed that they felt sometimes by answering: “Yes, sometimes.” 100% of the workers at S1 felt irritated stuffy nose, 60.6% (SWM), 57.6% (NEM) for S2, 62.5% (SWM), 50% (NEM) for S3, and 55.6% (SWM), 50% (NEM) for S4 with the answered: “Yes, sometimes.” Figure 4.3 also showed that a few workers never felt irritated stuffy nose with 24.2% (SWM), 33.3%(NEM) at S2, 12.5%(SWM), 37.5% (NEM) for S3 and 44.4% (SWM) and 16.7% (NEM) for S4 that answered: “No, never.”

Hoarse or dry throat is one of the symptoms asked in the questionnaire. 54.5% of the workers at S1 agreed that they felt hoarse or dry throat for both monsoonal seasons. 48.5% during SWM and 42.4% during NEM of S2 workers also answered “Yes, sometimes” for hoarse and dry throat symptoms. There were 37.5% (SWM), 56.25% (NEM) for S3 and 66.7% (SWM), and 44.4% (NEM) for S4 workers that agreed with the same answers, which are “Yes, sometimes.” There are a few workers who disagree that they felt hoarse or dry throat by answering “No, never,” with 27.3% for SWM and NEM at S1, 18.2% (SWM), 30.3% (NEM) for S2, 37.5% (SWM), 31.25% (NEM) for S3 and 16.7% (SWM), 11.1% (NEM) for S4.

The third last present symptom that was asked of workers was skin rashness or itchiness. Most of the workers answered “Yes, sometimes,” which showed that they faced skin rashness symptoms with 36.4%, 57.6% for both monsoonal seasons at S1 and S2, 50% during SWM, 6.25% during NEM for S3, 66.7% for SWM and 44.4% for NEM at S4. Few workers disagree by answering “No, never,” with 45.5%, 21.2% for SWM and NEM at S1 and S2, 18.8% (SWM), 87.5% (NEM) for S3, and 11.1% for SWM and 33.3% for NEM at S4.

Irritation of the eye showed that most workers agreed that they faced symptoms with the answer “Yes, sometimes.” with 36.4%, 60.6% of the workers at S1 and S2 during SWM, 50% (SWM), 25%(NEM) for S3 and 50% (SWM), 38.9%(NEM) for S4. Workers that answered “Yes, often” consisted of 27.3% and 21.2% for S1 and S2 during SWM and NEM, 50% during SW M for S3 and 11.1% (SWM), and 38.9% (NEM) for S4. Even though most workers faced eye irritation, a few disagreed with that statement and answered, “No, never.” with 36.4% (S1) and 18.2% (S2) for both monsoonal variations, 75% during NEM for S3 and 38.9% (SWM), 27.8% (NEM) for S4.

The last present symptoms were scaling and itching, to which most workers answered “No, never” felt those symptoms in the current situation. Percentages value in Table 4.3 shows that 72.7% of the workers at S1 during SWM and NEM, 24.2% (SWM), 36.4 (NEM) for S2, 25% (SWM), 100% (NEM) for S3 and 38.9% (SWM), 27.8% (NEM) for S4 that answer “No, never.” The rest of the workers believe they faced eye irritation with the answers “Yes, sometimes” or “Yes, often.” 9.1% of workers at S1 agreed that they faced irritation of the eye with the “Yes, sometimes” answer, 51.5% (SWM), 45.5% (NEM) for S2, 43.8% during SWM for S3 and 55.6% (SWM), 27.8% (NEM) for S4.

Table 4.3 Percentage of present symptoms among workers in each study area

Present Symptoms	S1		S2		S3		S4	
	SWM	NEM	SWM	NEM	SWM	NEM	SWM	NEM
Headache								
Yes, often (every week)	9.1	9.1	24.2	24.2	12.5	6.25	5.5	11.1
Yes, sometimes	72.7	72.7	33.4	33.4	68.8	87.5	66.7	66.7
No, never	18.2	18.2	42.4	42.4	18.8	6.25	27.8	22.2
Feeling heavy headed								
Yes, often (every week)	27.3	27.3	21.2	21.2	-	6.25	11.1	27.8
Yes, sometimes	45.5	45.5	36.4	36.4	43.8	25	55.6	50
No, never	27.3	27.3	42.4	42.4	56.3	68.75	33.3	22.2
Fatigue lethargy								
Yes, often (every week)	18.2	18.2	24.2	24.2	12.5	6.25	22.2	38.9
Yes, sometimes	63.6	63.6	48.5	48.5	75	93.75	66.7	50
No, never	18.2	18.2	27.3	27.3	12.5	-	11.1	11.1
Drowsiness								
Yes, often (every week)	9.1	9.1	27.3	24.2	25	-	22.2	38.9
Yes, sometimes	63.6	63.6	66.7	63.6	37.5	43.75	66.7	
No, never	27.3	27.3	6.1	12.1	37.5	56.25	11.1	61.1
Dizziness								
Yes, often (every week)			18.2	18.2	-	6.25		
Yes, sometimes	72.7	72.7	51.5	51.5	62.5	75	77.8	27.8
No, never	27.3	27.3	30.3	30.3	37.5	18.75	22.2	72.2
Nausea vomiting								
Yes, often	9.1	9.1			-	6.25		
Yes, sometimes	18.2	18.2	15.2	15.2	43.8	18.75	44.4	38.9
No, never	72.7	72.7	84.8	84.8	56.3	75	55.6	61.1
Cough								
Yes, often (every week)	18.2	18.2	15.2	6.1	-	12.5		
Yes, sometimes	63.6	63.6	54.5	45.5	62.5	18.75	11.1	55.6
No, never	18.2	18.2	30.3	48.5	37.5	68.75	88.9	44.4
Irritated stuffy nose								
Yes, often (every week)			15.2	9.1	25	12.5		33.3
Yes, sometimes (2-3 week)	100	100	60.6	57.6	62.5	50	55.6	50
No, never			24.2	33.3	12.5	37.5	44.4	16.7
Hoarse dry throat								
Yes, often (every week)	18.2	18.2	33.3	27.3	25	12.5	16.7	44.4
Yes, sometimes	54.5	54.5	48.5	42.4	37.5	56.25	66.7	44.4
No, never	27.3	27.3	18.2	30.3	37.5	31.25	16.7	11.1
Skin rash itchiness								
Yes, often (every week)	18.2	18.2	21.2	21.2	31.3	6.25	22.2	11.1
Yes, sometimes	36.4	36.4	57.6	57.6	50	6.25	66.7	55.6
No, never	45.5	45.5	21.2	21.2	18.8	87.5	11.1	33.3
Irritation of the eye								
Yes, often (every week)	27.3	27.3	21.2	21.2	50	-	11.1	33.3
Yes, sometimes	36.4	36.4	60.6	60.6	50	25	50	38.9
No, never	36.4	36.4	18.2	18.2	-	75	38.9	27.8
Scaling itching								
Yes, often (every week)	18.2	18.2	24.2	18.2	31.3	-	5.6	11.1
Yes, sometimes	9.1	9.1	51.5	45.5	43.8	-	55.6	61.1
No, never	72.7	72.7	24.2	36.4	25	100	38.9	27.8

The questionnaire consists of demographic factors, past 3-month symptoms, present symptoms and a section about workers' response to present symptoms. Table 4.4 shows that three questions were asked in this section. The first question asked about the opinion of workers if they said “Yes” or “Yes, sometimes” or “Yes, often” in the present symptoms section; this is due to the environment of the workstation or not. The answer provided to workers or respondents was “Yes” or “No”. Results from Table 4.4 showed that most workers agreed that the symptoms were due to the workplace environment, with 90.9% (S1) and 66.7% at both monsoonal seasons for S1 and S2 occupants answering “Yes” for these questions. 68.75% (SWM),81.25% (NEM) workers at S3 and 44.4%(SWM), 33.3% of workers inside S4 also answered “Yes” to these questions.

The next question was, “When do you experience relief from the symptoms?” and workers needed to answer either “After leaving the workplace”, “After leaving buildings”, or “Not sure”. Most of the workers answer, “After leaving the workplace”, with 63.6% for S1, 72.7% for S2, 50% (SWM) and 62.5% (NEM) for S3 and 44.4% for S4. The rest of the respondents answered, “After leaving the building”, except for 6.3% of occupants, who answered “Not sure” during southwest monsoon at S3.

The last question for this section was, “When do the symptoms occur?”. The workers agreed that the symptoms mainly occurred during “Lunch or evening”, with 45.5% for S1, 57.6% for S2, 81.25% for S3, 88.9% and 55.6% for S4. A few respondents agree the symptoms occurred during “Morning”, with 9.1% for S1,30.3% for S2 and 33.3% for NEM for S4. The rest of the workers answered “Not sure” with the question given. The percentage of respondents that answered “Not sure” was 45.5% for S1, 12.1% for S2, 18.75% for S3 and 11.1% for S4, as shown in Table 4.4.

Table 4.4 Percentage response of workers toward present symptoms

	S1		S2		S3		S4	
	SWM	NEM	SWM	NEM	SWM	NEM	SWM	NEM
If yes, this is due to the environment of the workstation								
Yes	90.9	90.9	66.7	66.7	68.75	81.25	44.4	33.3
No	9.1	9.1	33.3	33.3	31.25	18.75	55.6	66.7
When do you experience relief from the symptoms?								
After leaving workplace	63.6	63.6	72.7	72.7	50	62.5	55.6	55.6
After leaving the buildings	36.4	36.4	27.3	27.3	43.8	37.5	44.4	44.4
Not sure					6.3	-		
When do the symptoms occur?								
Morning	9.1	9.1	30.3	30.3	-	-	0	33.3
Lunch/Evening	45.5	45.5	57.6	57.6	81.25	81.25	88.9	55.6
Not sure	45.5	45.5	12.1	12.1	18.75	18.75	11.1	11.1
Number of occupants	11		33		16		18	

According to ICOP-IAQ (2010), the acceptable range for temperature is 23-26°C, relative humidity is 40-70%, and air movement is 0.15 to 0.50 m/s. The chemical parameters include formaldehyde (0.1ppm), carbon monoxide (10ppm), total volatile organic compound (3ppm), and interior air contaminants, including RSP (0.15mg/m^3). Indicators of ventilation performance include CO_2 (1000 ppm). Figures 4.3 a), 4.3 b), and 4.3 c) show a trend of SK Tanjung Gelam (S1) during the SWM and Figures 4.4 a), 4.3 b), and 4.4 c). The mean value was taken from 10 sampling days to determine compliance with the IAQ inside the study area. Figure 4.3 a) showed that SWM for temperature was between 27.62-30.84 ^{0}C for T, 72.92%-90.68% for RH, and air movement was the range between 0.148-0.695 m/s, while for northeast monsoon was in between 26.84-29.58 ^{0}C for temperature, 76.13-86.04% for relative humidity and 0.16-0.23 m/s for air movement (Figure 4.4a). The trend showed that physical parameters exceeded ICOP-IAQ (2010) standards, especially for T and RH. Movement trends for T and RH were inversely proportional, which showed that increasing temperature caused a decrease in the relative humidity value. Air movement values were insufficient almost constantly, below the standard range of 0.15-0.50 m/s.

Figures 4.3 b) and 4.4 b) showed chemical parameters for S1 for southwest and northeast monsoon. Figure 4.3 b) showed the SWM trend for CO (0.38-2.07ppm), CO_2 (365.73-417.17ppm), and HCHO (0.03 -0.04 ppm) and NEM chemical parameters were CO (0.08-0.58 ppm), CO_2 (408.44-470.22 ppm) and HCHO (0.018-0.020) at Figure 4.4 b). The trends showed compliance with physical parameters inside the room for both monsoons. HCHO came from furniture inside the rooms, and most of the furniture used pressed wood products. CO_2 comes from occupants inside the rooms, which consist of not more than 16 people. CO comes from cooking activities inside the rooms, such as water heaters and cooking apparatus such as air fryers and waffle makers. The reading of chemical parameters in NEM is higher than that of SWM.

Figures 4.3 c) and 4.4 c) display the trends in respirable suspended particles (RSP) for both the SWM and NEM. During SWM, the RSP levels ranged from 0.038 to 0.050 mg/m^3, while in NEM, they ranged from 0.025 to 0.035 mg/m^3. There was a noticeable slight decrease in RSP readings during the NEM, indicating a reduction in airborne particulate matter during this period. RSP levels in the building can be influenced by both internal and external factors. The internal sources primarily stem from the movements of occupants and teachers within the rooms, as their daily activities such as walking, shifting furniture, or engaging in classroom activities, stir up dust and particles that become airborne. Additionally, housekeeping practices within the building were rarely conducted, which could have contributed to the accumulation of particulate matter within the indoor environment. External sources of RSP can also contribute to the levels observed inside the rooms, particularly during times when ventilation is inadequate, or external air quality is poor. RSP can infiltrate the building from the outdoors, particularly when windows or vents are open or if the building is in an area with high levels of dust or vehicular emissions. The combination of these internal and external factors results in fluctuating RSP levels, which can affect indoor air quality and potentially influence the health and comfort of occupants. These findings highlight the importance of regular housekeeping and effective ventilation strategies to minimize RSP accumulation and ensure a healthier indoor environment.

a) b) c)

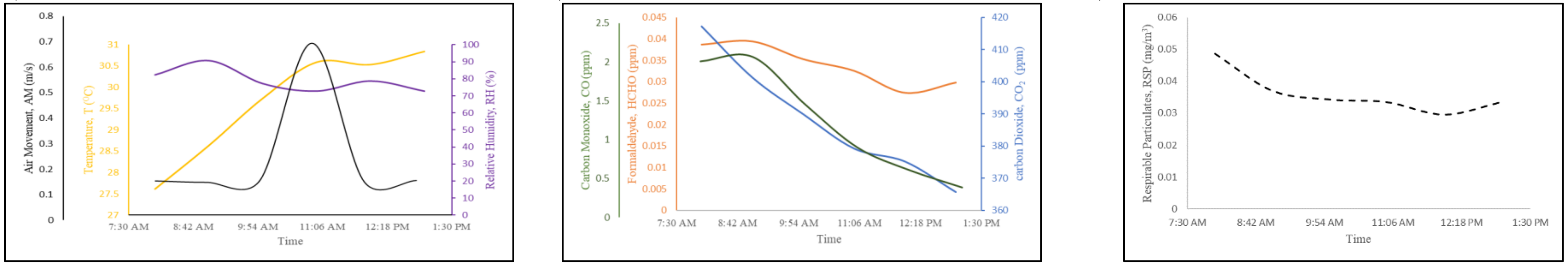

Figure 4.3 a) Physical parameters during SWM for S1; b) Chemical parameters during SWM for S1; c) Respirable Suspended Particulate during SWM for S1

a) b) c)

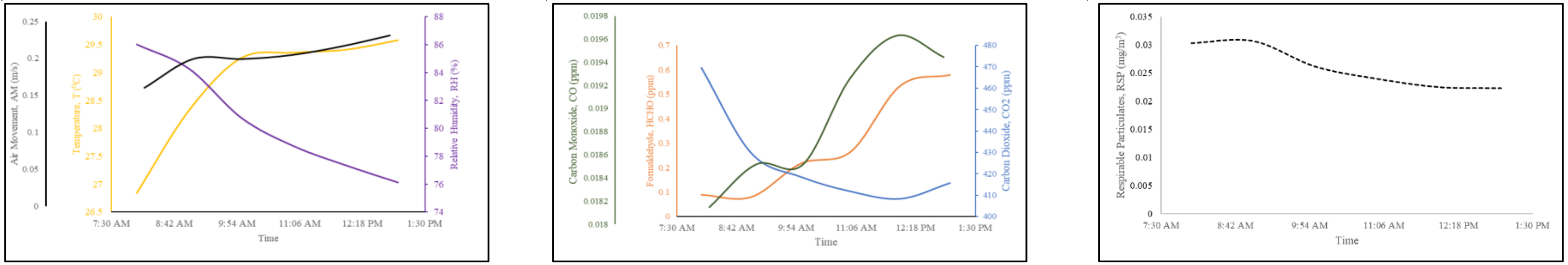

Figure 4.4 a) Physical parameters during NEM for S1; b) Chemical parameters during NEM for S1; c) Respirable Suspended Particulate during NEM for S1

Figures 4.5 and 4.6 show a physical, chemical, and RSP trend for TMG Mart Gong Badak. Figure 4.5 a) and Figure 4.6 a) showed that southwest monsoon for temperature was in between 27.62-29.93°C for temperature, 57.77-82.29% for relative humidity and air movement ranged between 0.07-0.16 m/s, while for northeast monsoon was in between 25.98-27.43 ^{0}C for temperature, 61.52-66.47% for relative humidity and 0.074-0.130 m/s for air movement. The trend showed that physical parameters exceeded ICOP-IAQ (2010) standards, especially for T and RH. The movement trend for T and RH was inversely proportional, which showed that increasing temperature caused a decrease in the relative humidity value. The temperature sparks between 1300 hours and 1400 hours inside the building due to many customers coming to buy groceries. Air movement values were insufficient almost constantly, below the standard range of 0.15 -0.50 m/s. Trends also showed that SWM is warmer than NEM reading of physical parameters.

The chemical parameters for S2 for the southwest and northeast monsoon were depicted in Figures 4.5 and 4.6 b). The SWM trend for CO_2 (464-587 ppm) and HCHO (0.02-0.04 ppm) was depicted in Figures 4.5 b), while the NEM chemical parameter was CO_2 (566-606 ppm) and HCHO (0.02-0.03). For both monsoons, the trends indicated that the physical parameters within the room were in accordance. HCHO is emitted by furniture within buildings. Within the buildings, CO_2 is generated by the occupants, which includes both customers and employees. Compared to SWM, the chemical parameter measurement in NEM is relatively high. Air pollutants with RSP trends are depicted in Figures 4.5 and 4.6 c). SWM's RSP trend ranged from 0.021 to 0.030 mg/m^3, while NEM's ranged from 0.014 to 0.027 mg/m^3). During the NEM, there was a modest decrease in the reading of RSP.

a) b) c)

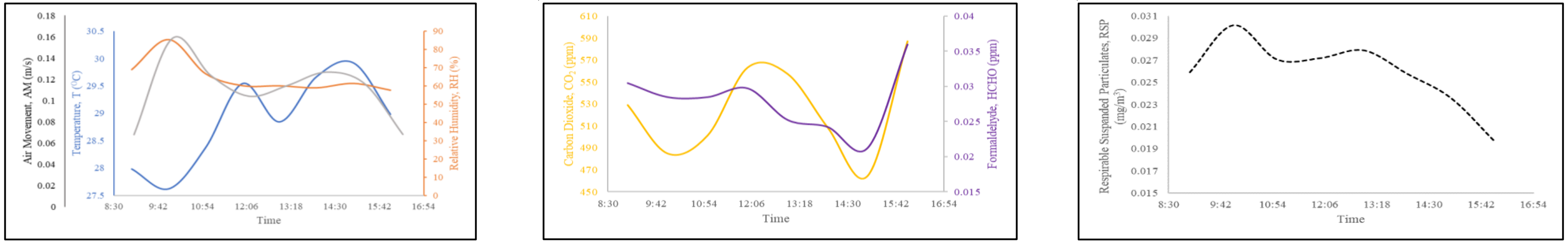

Figure 4.5 a) Physical parameters during SWM for S2; b) Chemical parameters during SWM for S2; c) Respirable Suspended Particulate during SWM for S2

a) b) c)

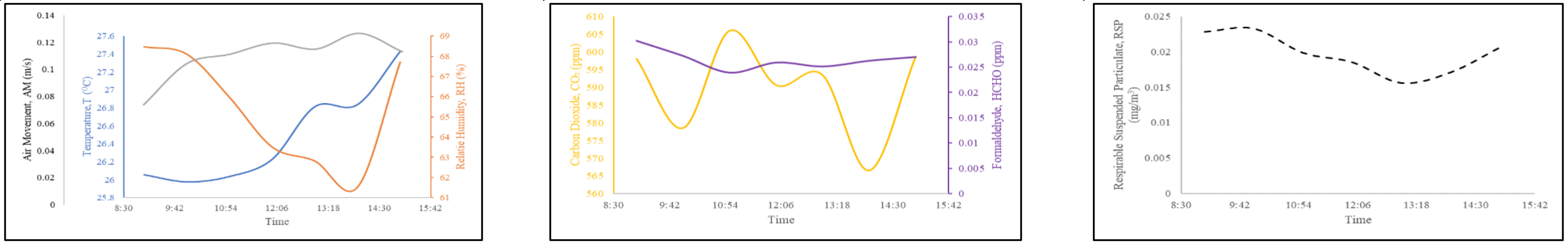

Figure 4.6 a) Physical parameters during NEM for S2; b) Chemical parameters during NEM for S2; c) Respirable Suspended Particulate during NEM for S2

The trends at Mset Inflatable Composit Corporation Sdn. Bhd (S3) during SWM and NEM are shown in Figures 4.7 and 4.8. During SWM, temperatures ranged from 27.12-32.91ºC, relative humidity from 68.25-89.57%, and air movement from 0.12-0.16 m/s (Figure 4.7 a). For NEM, temperatures ranged from 27.28-32.4ºC, relative humidity from 67.37-89.95%, and air movement from 0.139-0.228 m/s. Both monsoons exceeded ICOP-IAQ (2010) standards for temperature and relative humidity, with an inverse relationship between the two. Temperature peaks between 1400 and 1500 hours were due to intense activities like forklift operations, welding, painting, and sanding. Air movement remained insufficient during both monsoons due to confined spaces and limited operation of blowers. SWM was consistently hotter than NEM based on physical parameter readings.

During the SWM, the recorded CO_2 levels ranged from 312 to 326 ppm, total volatile organic compounds (TVOC) from 0 to 6.5 ppm, and formaldehyde (HCHO) from 0.01 to 0.14 ppm, as illustrated in Table 4.7 b). These values indicate a moderate range of chemical pollutants within the indoor environment during this monsoon. In contrast, the NEM showed elevated levels for the same parameters, with CO2 ranging from 320 to 363 ppm, TVOC from 0 to 0.19 ppm, and HCHO from 0.019 to 0.052 m/s, as depicted in Table 4.8 b). The rise in chemical parameter readings during NEM suggests a more pronounced accumulation of pollutants, possibly due to differing ventilation dynamics or external environmental factors that influence indoor air conditions during this period. The presence of TVOC and HCHO, which are common indoor air pollutants, underscores the importance of effective ventilation and source control in maintaining IAQ. The comparison between the two monsoons reveals that while the physical parameters of the buildings complied with both monsoon periods, the elevated chemical parameters during NEM highlight a need for enhanced monitoring and mitigation strategies during this season. During SWM, the RSP levels fluctuated between 0.04 to 0.134 mg/m³, whereas during NEM, they ranged from 0.05 to 0.32 mg/m³. These findings emphasize the variability of indoor air quality parameters across different monsoonal periods and the need for tailored IAQ management practices that account for seasonal changes. Understanding the trends in chemical parameters and RSP levels during SWM and NEM allows for more targeted interventions.

a) b) c)

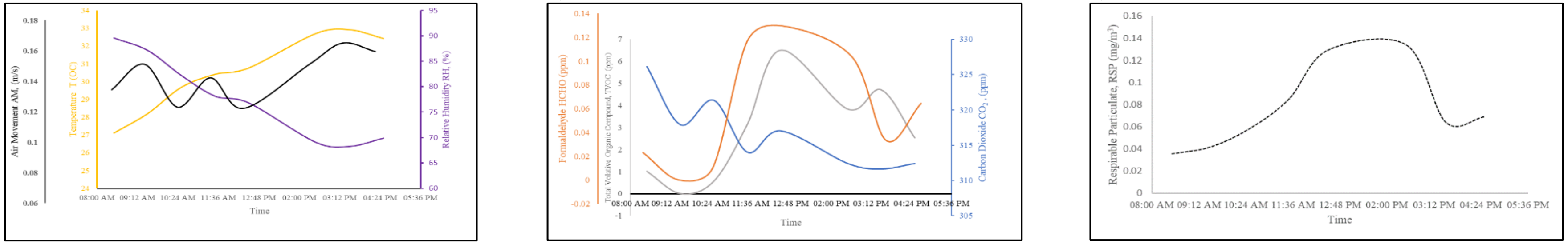

Figure 4.7 a) Physical parameters during SWM for S3; b) Chemical parameters during SWM for S3; c) Respirable Suspended Particulate during SWM for S3

a) b) c)

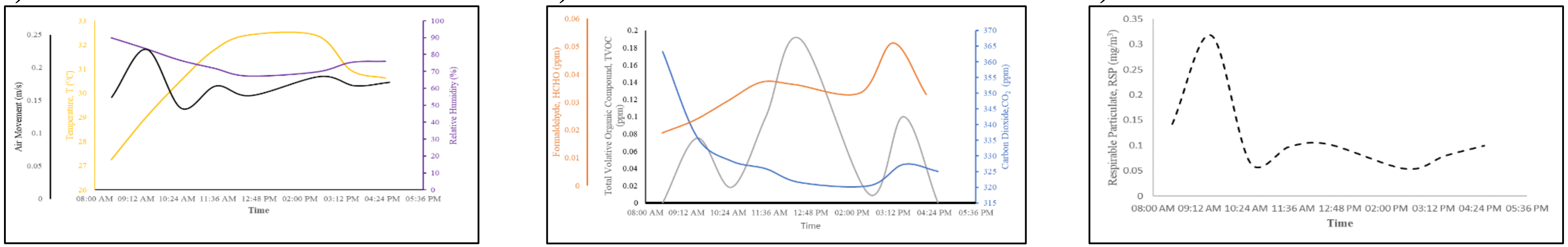

Figure 4.8 a) Physical parameters during NEM for S3; b) Chemical parameters during NEM for S3; c) Respirable Suspended Particulate during NEM for S3

The Raia Hotel & Convention Centre Terengganu (S4) trend is illustrated in Figures 4.9 and 4.10. The SWM was characterised by a temperature (T) ranging from 24.20 to 25.36 0C, a relative humidity (RH) of 69.15 to 71.2%, and an air movement of 0.09 to 0.12 m/s. The northeast monsoon was characterised by a temperature (T) ranging from 23.5-24.2ºC, a relative humidity of 67.19 to 71.6 %, and an air movement of 0.10-0.13 m/s. These findings are illustrated in Figures 4.9 a) and 4.10 b). The trend indicated that the physical parameters, particularly the relative humidity, exceeded the standards established by the ICOP-IAQ (2010). The movement trend for T and RH was inversely proportional, indicating that the relative humidity value decreased as the temperature increased. The air movement values were insufficient, falling below the standard range of 0.15 to 0.50 m/s. Additionally, the trends indicated that the SWM was hotter than the NEM reading of the physical parameters.

The chemical parameters and ventilation performance indicators for S4 in SWM and NEM were presented in Tables 4.9 and 4.10. Table 4.9 b) displayed the SWM trend for CO_2 (550.19-674.22 ppm) and the NEM ventilation performances indicator for CO_2 (501-643 ppm). The trends indicated that the ventilation performance indicator complied within the chamber during both monsoons. CO_2 is generated by individuals who reside within the study area. The ventilation efficacy indicator reading in the NEM is lower than that of the SWM. Air pollutants with respirable suspended particulates (RSP) trend are depicted in Figures 4.9 b) and 4.10 b). SWM's RSP trend ranged from 0.021 to 0.035 mg/m^3, while NEM's ranged from 0.026 to 0.037 mg/m^3. During NEM, there was a modest increase in the reading of RSP. The RSP is derived from the movements of individuals within the study area. The frequent door opening allows RSP to enter the study area inside and outside.

a) b)

Figure 4.9 a) Physical parameters during SWM for S4; b) Chemical parameters during SWM for S4

a) b)

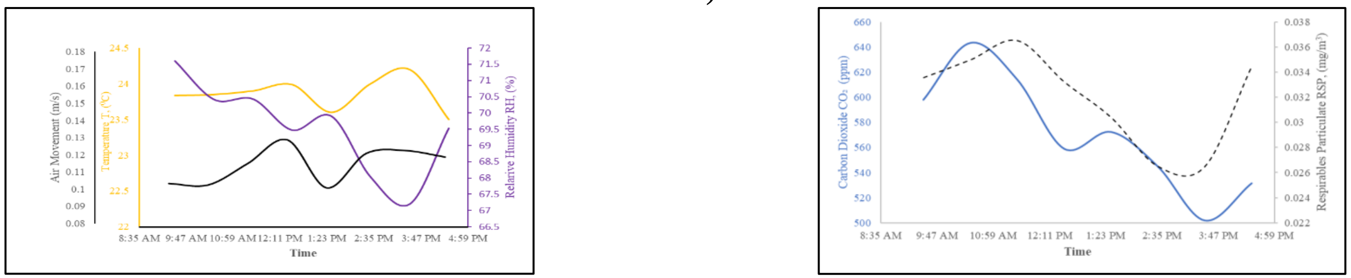

Figure 4.10 a) Physical parameters during NEM for S4; b) Chemical parameters during NEM for S4

Indoor-outdoor ratios (I/O ratios) for each study area with distinct monsoonal seasons are illustrated in Table 4.5. The indoor-outdoor ratio assesses the disparity between the indoor concentration and the corresponding outdoor levels. The I/O ratios of 1.2 or greater indicate that the indoor concentration exceeds that of the outdoors and may be attributed to indoor sources. I/O ratios of 0.8-1.2 indicate that the indoor concentration is equivalent to that of the outdoors, and I/O ratios of 0.8 or less suggest that the indoor concentration is less than that of the outdoors, illustrating the possibility of outdoor influence.

Table 4.5 indicates that the interior and outdoor air concentrations in SK Tanjung Gelam (S1) were nearly identical, except for CO in SWM. The I/O ratio was more significant than 1.2 due to the occupants cooking in the instructors' rooms, which resulted in a dominant indoor concentration. According to TMG Mart (S2), the operational air conditioning in the study area was inadequate for ventilation within the study area, resulting in AM values of 3.74 (NEM) and 2.69 (SWM) for each monsoonal season, which exceeded 1.2. The study area was expansive, and the operating air conditioning was inadequate, as it was only functioning on four occasions.

Mset Inflatable Composit Corporation Sdn. Bhd. (S3) was one of the boat-making companies. The I/O ratio indicated that indoor and outdoor air intrusion was equivalent, except TVOC, which was derived from indoor sources. These sources included resin, paint, paint thinner, and aldehydes, which were used in the production of boats during both monsoons. The I/O ratios were 1.48 (NEM) and 1.52 (SWM). The physical parameters of Raia Hotel & Convention Centre Terengganu (S4) were more significant than 1.2, indicating that indoor sources were the dominant factor. This was attributed to the use of air conditioning during both the SWM and NEM monsoons. The indoor concentration of CO_2 was equivalent to that of the outdoor concentration during both monsoons, with an I/O ratio of 0.92. The I/O ratio for RSP was also equivalent between 0.8 and 1.2.

Table 4.5 I/O ratio for Northeast Monsoon and Southwest Monsoon

		T	RH	AM	TVOC	HCHO	CO	CO_2	RSP
S1	NEM	1.00	1.01	0.66	**-**	1.07	1.09	1.14	0.995
	SWM	0.87	0.99	0.96	-	0.98	**1.55**	1.03	1.00
S2	NEM	**1.25**	1.09	**3.74**	-	**1.51**	-	0.85	0.96
	SWM	1	1.12	**2.69**	-	0.97	-	0.93	1.13
S3	NEM	1.01	0.98	1.00	**1.48**	1.02	-	1.02	**1.38**
	SWM	1.00	0.99	0.94	**1.52**	0.9	-	1.01	**1.43**
S4	NEM	1.06	**1.96**	**1.64**	-	-	-	0.92	1.09
	SWM	**1.92**	**1.24**	**1.54**	-	-	-	0.92	0.85

4.1.2 Simulation of Computational Fluid Dynamics

Complex mathematical equations describing the behaviour of fluids are solved using computer-based approaches in CFD based modelling. These simulations offer quantitative and qualitative insights into the dispersion of radioactive gasses in a particular environment. This is accomplished by combining numerical methods, such as separation and solution techniques, mathematical modelling, which applies partial differential equations (PDE), and specialised software tools, such as solvers, preprocessing utilities, and post-processing utilities. Methodically, the analytical process in CFD modelling consists of multiple stages, and the output is shown in Figure 4.11-4.18. Simulation of CFD for SK Tanjung Gelam (S1) is shown in Figure 4.11-Figure 4.12. Data used consists of 9 days sampling period and for validation used one remaining sampling period

Figures 4.11 and 4.12 illustrate the airflow patterns predicted by the CFD numerical simulation for the NEM and SWM at SK Tanjung Gelam (S1). The simulation reveals that fresh air introduced through the inlet circulates within the teacher's room, blending with the air exhaled by the occupants. This is depicted by the vectors showing airflow velocity along the streamlines. As the airflow progresses through the room and moves toward the outlet, a decrease in velocity is observed downstream. The velocity distribution at a cut plane near the ventilation fan indicates significant pressure and velocity gradients around S1. The contour map of turbulent kinetic energy at this cut plane highlights high turbulence near the mechanical ventilation for both monsoons. The simulation accuracy was 91.9% for SWM and 89.57% for NEM compared to the measured values from SK Tanjung Gelam. The fan's clockwise rotation and the dispersion effects due to open windows and doors in the teacher's room were also demonstrated in the simulation. R^2 values for observed versus predicted values from simulations across each study area shown at Figure 4.19.

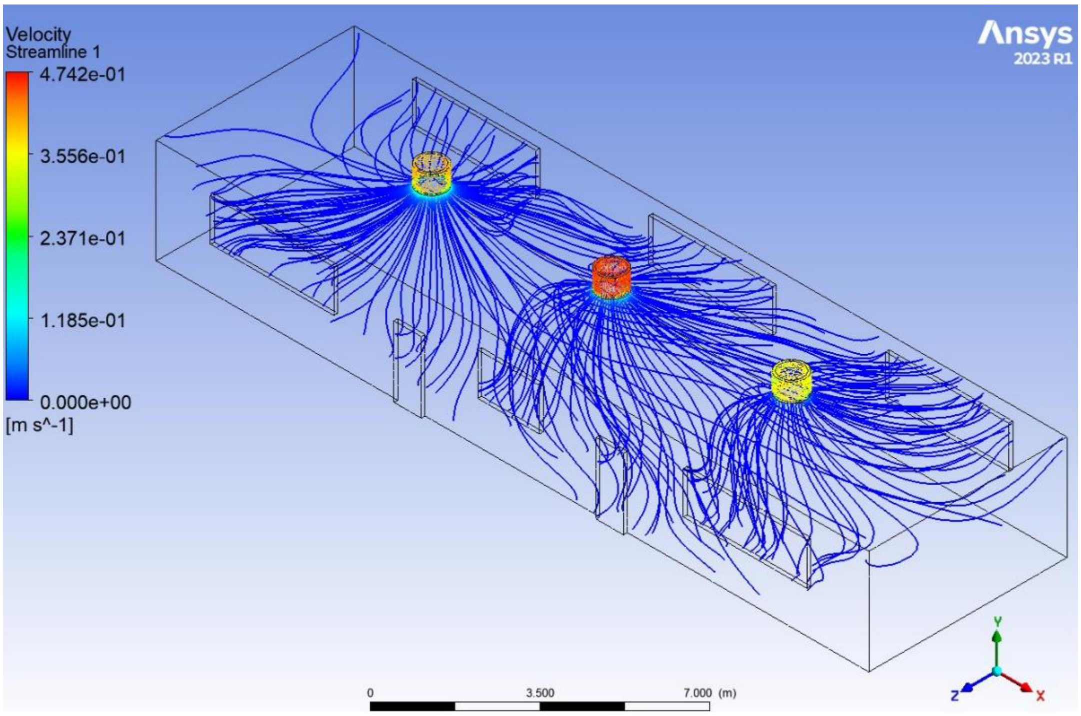

Figure 4.11 SK Tanjung Gelam (S1)-Southwest Monsoon

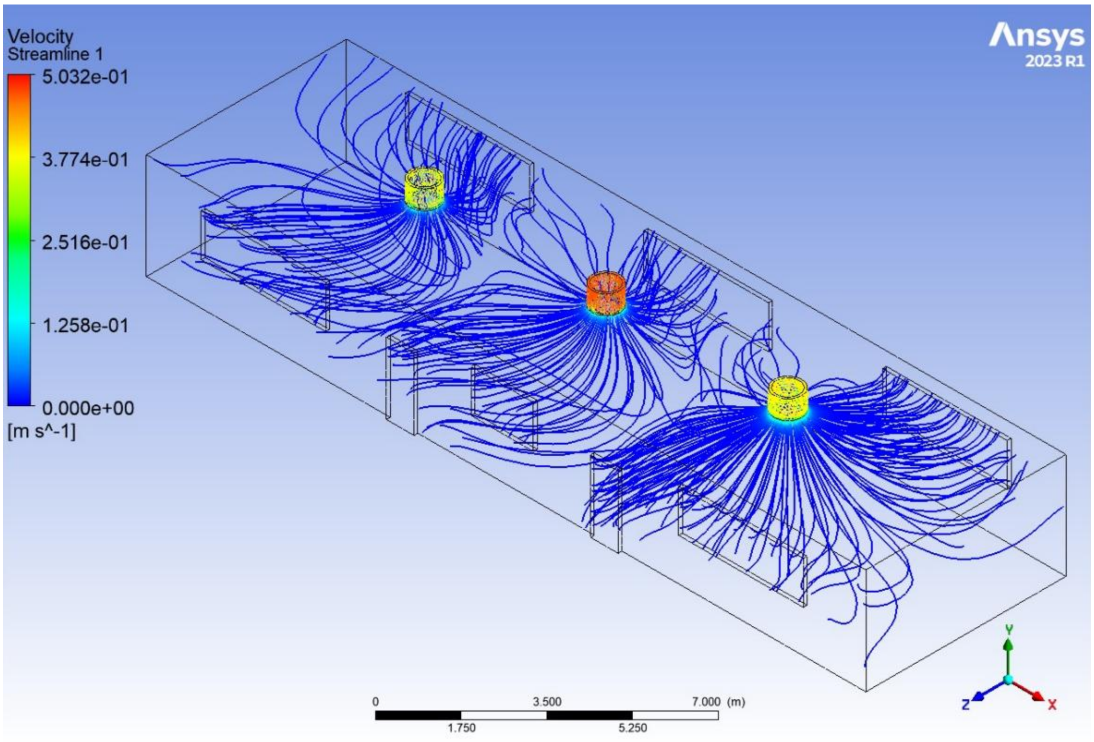

Figure 4.12 SK Tanjung Gelam (S1)- Northeast Monsoon

Figure 4.13 shows a simulation of TMG Mart (S2) for SWM, and Figure 4.14 shows simulation S2 for NEM. The supermarket interior was circulated by the fresh air injected from the inlet, which was diverted downward and combined with the air the workers breathed. It shows the vectors of airflow velocity along the room's airflow streamlines. While the airflow moved through the supermarket layout and then toward the outlet, it was noticed that the downstream airflow velocity reduced. The shape of airflow velocity is at a cut plane near the ventilation, which is air conditioning. Around the S2, significant pressure and velocity gradients in the air were noted. The contour of turbulent airflow kinetic energy is shown at the cut plane. The vicinity of the mechanical ventilation was found to have high turbulent kinetic energy for both monsoons. The accuracy of the simulation for SWM at the study area was 77.75% and 70.64% for NEM compared with the sampling value conducted in the TMG Mart. Air movement in the study area was shown in the simulation, and dispersion was not widespread in the study area, especially at the center of the study area (S2).

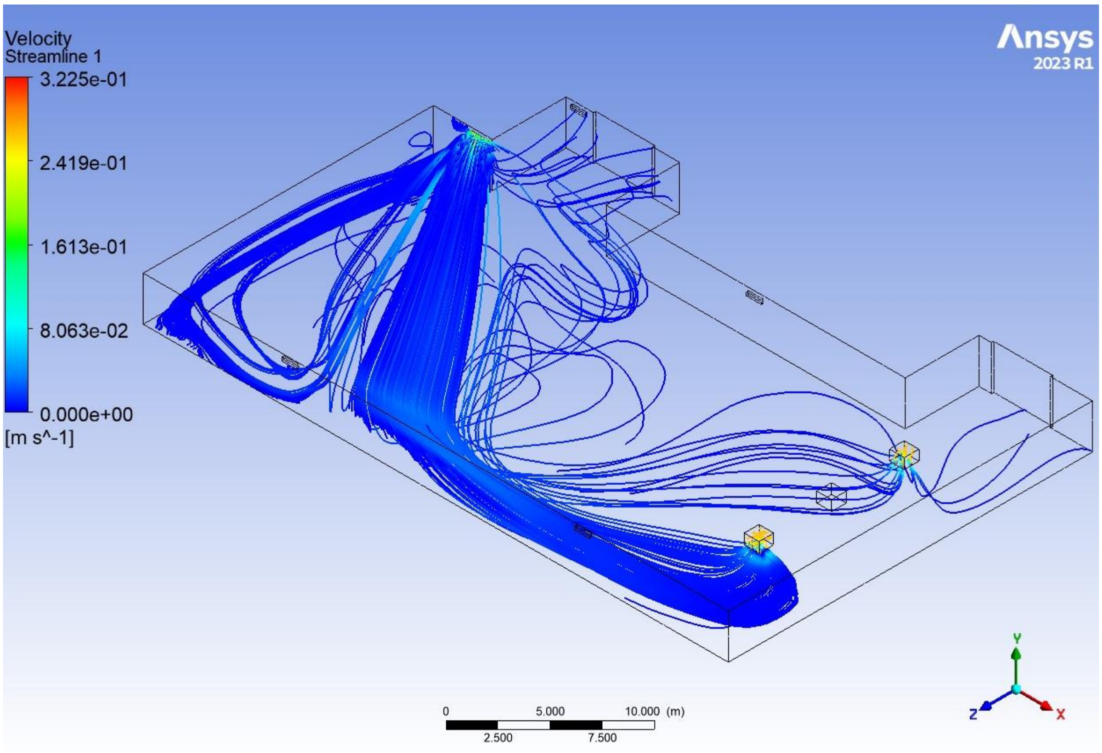

Figure 4.13 TMG Mart (S2)-Southwest Monsoon

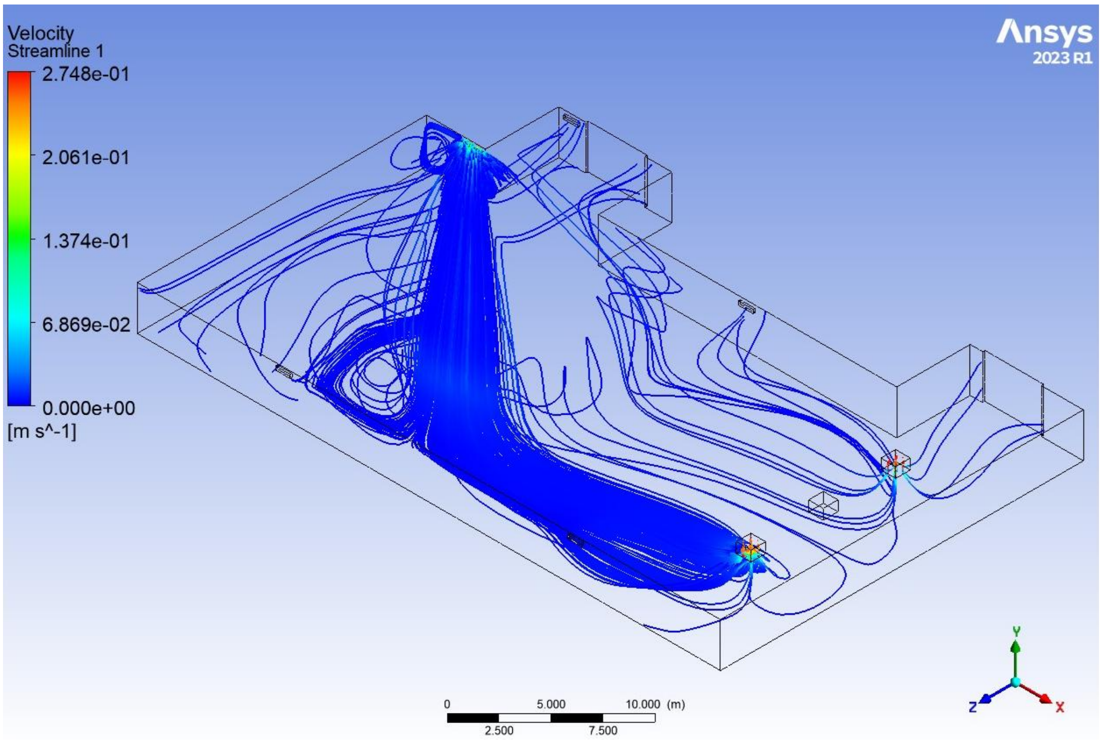

Figure 4.14 TMG Mart (S2)-Northeast Monsoon

Mset Inflatable Composite Corporation Sdn. Bhd. (S3) is simulated in Figure 4.15 for the SWM, while Figure 4.6 illustrates the simulation of S3 for the NEM. The fresh air injected from the inlet was diverted downward and combined with the workers inhaled air to circulate the ship's manufacturing interior. It displays the vectors of airflow velocity along the warehouse airflow streamlines. The downstream airflow velocity decreased as the airflow progressed through the warehouse layout and toward the outflow. The shape of airflow velocity at a cut plane near the ventilation system, which is a blower. Significant pressure and velocity gradients in the air were observed near the S3. The kinetic energy contour of turbulent airflow is illustrated. The turbulent kinetic energy near the mechanical ventilation was high during both monsoons compared to the sampling value conducted by Mset Inflatable Composit Corporation Sdn. Bhd., the simulation's accuracy for SWM in the study area was 88.06%, and for NEM, it was 86.62%. The simulation depicted air movement in the study area, and dispersion was not prevalent in the study area, particularly at the centre (S3). In addition to loading and unloading materials for boat construction, the warehouse was equipped with open ventilation and a large door that enabled forklifts to convey the product, a manufactured fibre boat. Based on the simulation, the warehouse's airflow was sufficient to reach all areas. The only side that lacked airflow was the one that contained the boat mould.

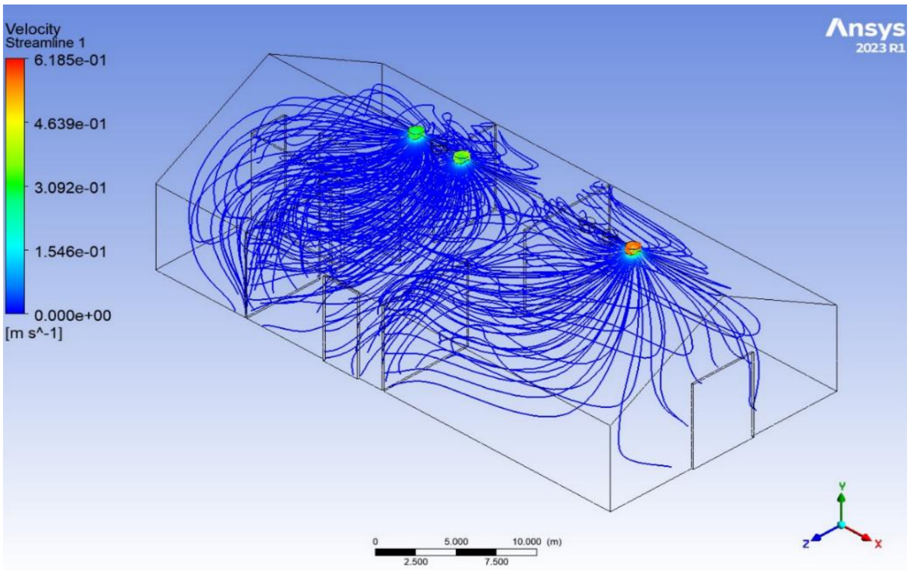

Figure 4.15 Mset Inflatable Composit Corporation Sdn. Bhd. (S3)-Southwest Monsoon

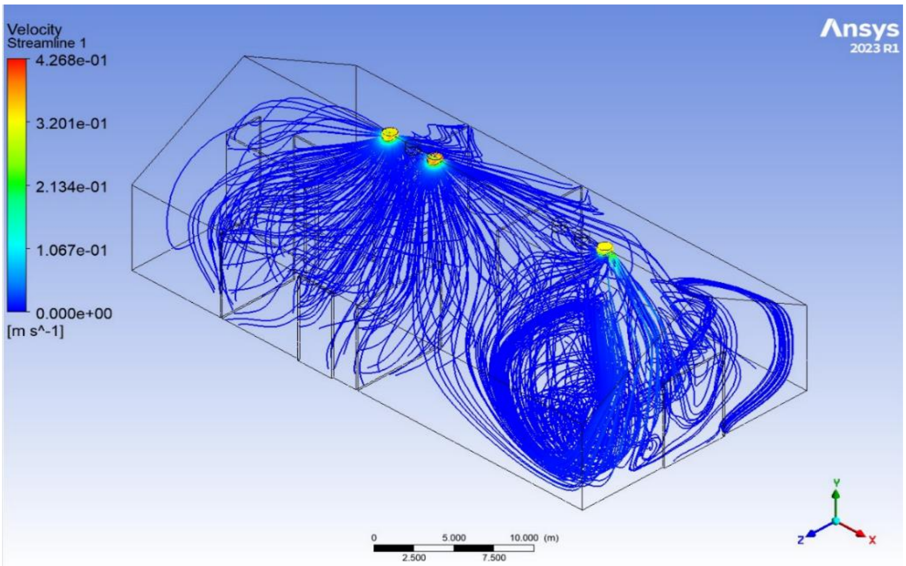

Figure 4.16 Mset Inflatable Composit Corporation Sdn. Bhd. (S3)- Northeast Monsoon

The simulation of Raia Hotel & Convention Centre Terengganu (S4) for SWM is depicted in Figure 4.17, while the simulation of S4 for NEM is in Figure 4.18. The fresh air injected from the inlet was diverted downward and combined with the workers' inhaled air to circulate the hotel's interior. It displays the vectors of airflow velocity along the airflow streamlines of the room. It was observed that the downstream airflow velocity decreased as the airflow progressed through the hotel layout and toward the outflow, the shape of airflow velocity at a cut plane near the ventilation system, which is air conditioning. Significant pressure and velocity gradients in the air were observed near the S4. The turbulent kinetic energy near the mechanical ventilation was high during both monsoons. Compared to the sampling value obtained at the Raia Hotel & Convention Centre Terengganu (S4), the simulation's accuracy for SWM at the study location was 89% and 91.17% for NEM. The observed effects of the fan movement and room openings also help us understand how these factors influence airflow distribution and ventilation efficiency. Figure 4.18 showed the performance of the system was evaluated across four study sites (S1, S2, S3, and S4) during the SWM and NEM seasons. The highest performance was observed at Site S1, with values of 91.90% for SWM and 89.57% for NEM. Site S2 recorded the lowest performance, with 77.75% during SWM and 70.64% during NEM. Sites S3 and S4 demonstrated consistently high performance, with values exceeding 86% for both monsoons. These results indicate that site-specific factors may influence the performance metrics during different monsoon seasons.

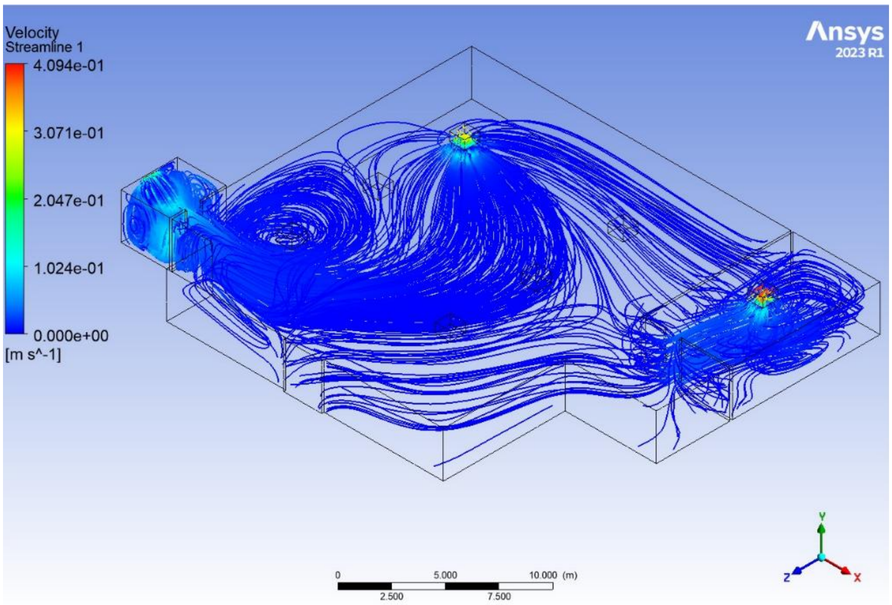

Figure 4.17 Raia Hotel & Convention Centre Terengganu (S4)-Southwest Monsoon

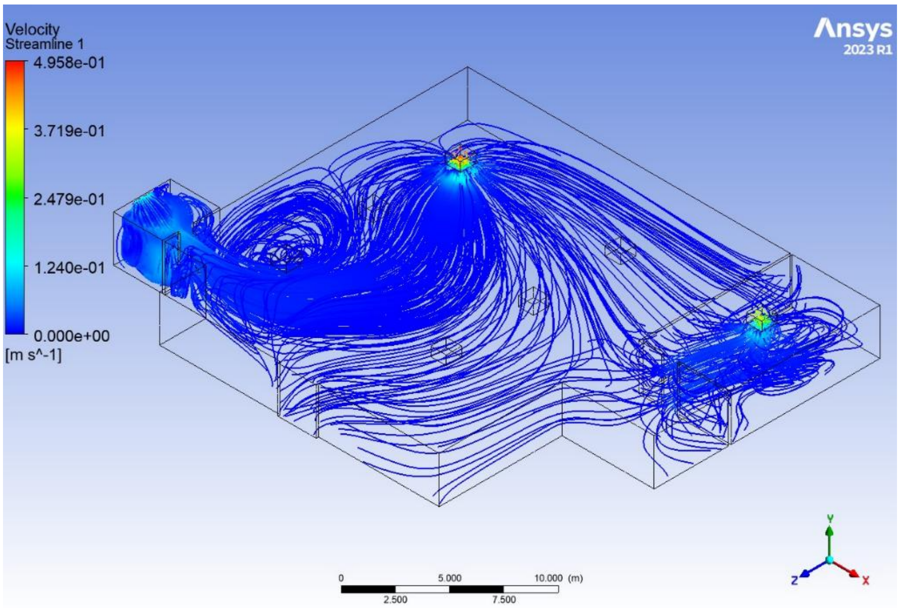

Figure 4.18 Raia Hotel & Convention Centre Terengganu (S4)-Northeast Monsoon

Site/ Monsoon	SWM	NEM
S1	91.90%	89.57%
S2	77.75%	70.64%
S3	88.06%	86.62%
S4	89.00%	91.17%

Figure 4.19 R^2 values for observed versus predicted values from simulations across each study area.

4.1.3 Principal Component Analysis (PCA)

Table 4.6 shows the KMO and Bartlett's Test values for all sites. The KMO and Bartlett's Test values satisfy the PCA requirement in Table 4.6. All sites showed the adequacy of the data, with a range of 0.440 to 0.702 for the KMO Test. Acceptability or adequacy of the data set must be more than 0.5, and the results of KMO showed that the data can proceed with PCA. Bartlett's test showed a significant value smaller than 0.05 (p-value<0.05), which is 0.00 at all sites. Both tests showed that all data sets showed the full-fill requirement for PCA.

Table 4.6 KMO and Bartlett's Test

Study area	**Monsoon**	**Kaiser-Meyer-Olkin Measure of Sampling Adequacy.**	**Bartlett's Test of Sphericity (Sig)**
S1	SWM	0.702	0.000
	NEM	0.523	0.000
S2	SWM	0.456	0.000
	NEM	0.440	0.000
S3	SWM	0.532	0.000
	NEM	0.590	0.000
S4	SWM	0.560	0.000
	NEM	0.533	0.000

Then, the analysis proceeds with commonalities shown in Table 4.7. The initial value showed a value of 1.00 for all parameters. Extraction values in communalities tables were crucial as only the parameter with more than 50% variance in the data set was considered for further analysis. Otherwise, it was removed, and the KMO and Bartlett's tests were rechecked until all input parameters had more than 50% variance contribution in the data set, as shown in Table 4.7. Table 4.7 shows that all parameters contribute more than 50% and proves that all parameters significantly impact the formation of poor IAQ in the study area. Table 4.7 showed that S1 has extraction value ranged 0.136-0.726 for SWM and 0.552-0.767 for NEM, S2 ranged 00.585-0.808 for SWM and 0.568-0.731 for NEM, S3 ranged 0.610-0.964 for SWM and 0.458-0.875, S4 ranged 0.319-0.652 for SWM andutilising586 for NEM. This showed that all parameters have more than 50% variance contribution.

Table 4.7 Communalities

SK TANJUNG GELAM (S1)				
	SWM		NEM	
	Initial	Extraction	Initial	Extraction
T	1.000	.707	1.000	.732
RH	1.000	**.726**	1.000	.577
AM	1.000	**.136**	1.000	.572
CO_2	1.000	.442	1.000	**.552**
CO	1.000	.619	1.000	.751
HCHO	1.000	.462	1.000	**.767**
RSP	1.000	.582	1.000	.731
TMG (S2)				
	SWM		NEM	
	Initial	Extraction	Initial	Extraction
T	1.000	**.808**	1.000	.693
RH	1.000	.772	1.000	**.731**
AM	1.000	**.585**	1.000	**.568**
CO_2	1.000	.766	1.000	.629
HCHO	1.000	.619	1.000	.634
RSP	1.000	.772	1.000	.614
MSET (S3)				
	SWM		NEM	
	Initial	Extraction	Initial	Extraction
T	1.000	**.964**	1.000	**.875**
RH	1.000	.960	1.000	.838
AM	1.000	.804	1.000	.607
CO_2	1.000	.743	1.000	.495
HCHO	1.000	**.610**	1.000	**.458**
TVOC	1.000	.714		
RAIA HOTEL (S4)				
	SWM		NEM	
	Initial	Extraction	Initial	Extraction

T	1.000	.556	1.000	**.466**
RH	1.000	.597	1.000	.568
AM	1.000	**.319**	1.000	.488
RSP	1.000	.608	1.000	.550
CO_2	1.000	**.652**	1.000	**.586**

Extraction Method: Principal Component Analysis.

Table 4.8-4.11 lists the eigenvalues related to each linear component before extraction and after rotation. Before extraction, linear components are perceived separately inside the instructive list for S1, S2, S3, and S4. The eigenvalues related to each component or also called as factor address the distinction cleared up by that linear component and demonstrate their eigenvalue in terms of the percentage of variance explained. PCA separates all elements with eigenvalues of more than 1. Utilising two factors, the variability was around 49.243%(S1) and 54.046% (S4) for SWM and 65.453% (S3) and 53.143% (S4) for northeast monsoon. Other sites utilising three factors which are 64.025% (S1), 64.490% (S2) for NEM, 70.342% (S2), and 79.943% (S3) for SWM.

The rotation has the effect of enhancing the factor structure and one outcome for this data. This shows that the relative hugeness of the three components is levelled. Before rotation, factor 1 (34.434%) represented significantly more difference than the other factor 2 (14.829%) for S1 for SWM and factor 1(28.182%), factor 2 (19.024) and factor 3 (16.819%) for NEM which showed in Table 4.8. However, after extraction, there are slightly increasing and decreasing factor contributions such as factor 1(31.389%) and factor 2 (17.873%) for SWM for S1 at row rotation sums of squared loadings row at % of variances for S1 and factor 1 (27.315%), factor 2 (18.919%) and factor 3 (17.792%) for NEM.

Table 4.8 Total Variance Explained (S1)

SOUTHWEST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	2.755	34.434	31.389	31.389
2	1.186	14.829	17.873	49.263
3	.978			

4	.859
5	.760
6	.725
7	.494
8	.243

NORTHEAST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	1.973	28.182	27.315	27.315
2	1.332	19.024	18.919	46.234
3	1.177	16.819	17.792	64.025
4	.875			
5	.746			
6	.492			
7	.404			

Before rotation, factor 1 (31.134%) represented significantly more difference than the other factor 2 (20.602%) and factor 3 (18.606%) for S2 (SWM), while factor 1(26.6%), factor 2 (20.546%) and factor 3 (17.343%) for NEM which showed in Table 4.9. However, after extraction, there are slightly increasing and decreasing factor contributions such as factor 1(27.915%), factor 2 (22.635%) and factor 3 for SWM at S1 at row rotation sums of squared loadings row in column % of variances for S2. After extraction, there are slightly increasing and decreasing factor contributions such as factor 1 (25.553%), which decrease from extraction before this in factor 1 (26.6%), factor 2 (19.866%), which decrease from previous extraction for factor 2 which 19.866% and increasing rotation from 17.343% to 19.071% for factor 3 at S2 during northeast monsoon.

Table 4.9 Total Variance Explained (S2)

SOUTHWEST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	1.868	31.134	27.915	27.915
2	1.236	20.602	22.635	50.550
3	1.116	18.606	19.792	70.342
4	.739			

5	.701			
6	.339			

NORTHEAST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	1.596	26.600	25.553	25.553
2	1.233	20.546	19.866	45.418
3	1.041	17.343	19.071	64.490
4	.915			
5	.771			
6	.445			

During the southwest monsoon (SWM), factor 1 (37.960%), factor 2 (23.979%), and factor 3 (18.004%) accounted for the majority of the variance (% of variance) in the extraction sum of squared loading for S3 (Figure 4.10). After the rotation, the value of factor 1 decreased from the previous value by 35.79%, while factor 2 and factor 3 increased by 24.169% and 19.984%, respectively. The Northeast monsoon (NEM) demonstrated that factor 1 (43.727%) represented a substantially more significant difference than factor 2 (21.726%) before rotation. After extraction, the factor contributions are marginally increasing and decreasing, with factor 1 (42.583%) exhibiting a decreasing value and factor 2 (22.870%) increasing value during NEM in S3.

Table 4.10 Total Variance Explained (S3)

SOUTHWEST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	2.278	37.960	35.790	35.790
2	1.439	23.979	24.169	59.959
3	1.080	18.004	19.984	79.943
4	.657			
5	.533			
6	.014			
NORTHEAST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	

	Total	% of Variances	% of Variance	Cumulative %
1	2.186	43.727	42.583	42.583
2	1.086	21.726	22.870	65.453
3	.893			
4	.702			
5	.132			

Table 4.11 presents the total variance explained for both the SWM and NEM. In the case of the SWM the first component has an initial eigenvalue of 1.575 and explains 31.504% of the variance, which reduces slightly to 31.415% after extraction, contributing to a cumulative variance of 31.415%. The second component has an initial eigenvalue of 1.157, explaining 23.143% of the variance, and after extraction, it accounts for 23.231%, bringing the cumulative variance explained to 54.646%. Components three, four, and five have eigenvalues less than 1, indicating minimal contributions to the total variance, thus they are not extracted or rotated.

For the NEM, the first component shows an initial eigenvalue of 2.186, accounting for 28.561% of the variance, which adjusts to 28.523% post-extraction, resulting in a cumulative variance of 28.523%. The second component, with an initial eigenvalue of 1.086, explains 24.582% of the variance, which slightly increases to 24.620% after extraction, leading to a cumulative variance of 53.143%. Similarly, components three, four, and five in the Northeast Monsoon have eigenvalues less than 1, making their contribution to the variance negligible, and they are not further analysed. Overall, two components in both monsoons collectively explain over 50% of the variance, with the first component contributing the most.

Table 4.11 Total Variance Explained (S4)

SOUTHWEST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	1.575	31.504	31.415	31.415
2	1.157	23.143	23.231	54.646
3	.937			
4	.746			
5	.585			

NORTHEAST MONSOON				
Component	Initial Eigenvalues	Extraction Sum of squared loading	Rotation Sum of Squared Loadings	
	Total	% of Variances	% of Variance	Cumulative %
1	2.186	28.561	28.523	28.523
2	1.086	24.582	24.620	53.143
3	.893			
4	.702			
5	.132			

This table 4.12 presents the rotated component matrix from a Principal Component Analysis (PCA), which identifies underlying relationships between variables across different study areas during two distinct monsoon seasons: Southwest Monsoon (SWM) and Northeast Monsoon (NEM). The study areas include SK Tanjung Gelam (S1), TMG (S2), MSET (S3), and Raia Hotel (S4). The analysis is performed for four study areas (S1, S2, S3, S4). Each area is analysed separately for two seasons which consists of SWM and NEM. There are components which each variable's loading value indicates how strongly it is associated with a particular component. Components 1, 2, and 3 represent the key latent factors extracted through PCA. Variable loadings show a high positive or negative value (close to ±1) indicates a strong correlation between the variable and the component. Values below ±0.4 are generally considered weak and insignificant. Rotation method uses Varimax with Kaiser Normalization to rotate components, enhancing interpretability by maximizing variance between variables.

SK Tanjung Gelam (S1) results during SWM showed Component 1 consists of Temperature (T) has a strong negative loading (-0.840), while RH (0.822) and CO2 (0.610) have strong positive loadings while Component 2 consists of CO (0.775) and HCHO (0.642) are strongly correlated. During NEM showed Component 1 was Temperature (T, 0.841) and RSP (0.831) dominate with strong positive loadings and Component 2 was CO2 (-0.702) and RH (-0.625) show significant negative correlations. TMG (S2) results from Table 4.12 during SWM has 2 components which Component 1 consists of Temperature (T, -0.891) shows a strong negative correlation, while RH (0.776) and AM (0.684) are positively associated, and Component 2 involves of HCHO (0.603) and RSP (0.878) are highly correlated with this component while during NEM there are 2 components. Component 1 contain RH (0.843), AM (0.733), and

Temperature (T, 0.682) are strongly correlated and Component 2 occupies HCHO (0.769) dominates. Third study area was MSET which during SWM consists of 2 significant components. Component 1 has Temperature (T, 0.979) and RH (-0.974) are strongly associated, indicating an inverse relationship and Component 2 consists of HCHO (0.862) and TVOC (0.831) dominate this component and during NEM, Component 1 has RSP (0.987) and CO2 (0.666) have strong positive loadings and Component 3 has RH (0.893) and AM (-0.771) dominate. Last study areas were Raia Hotel (S4) which during SWM has Component 1 that involves RSP (0.705) is strongly associated with this component and Component 2: RH (0.762) and CO2 (-0.803) dominate, with CO_2 showing an inverse relationship. During NEM S4 has 2 component which Component 1 has RH (0.752) and CO2 (0.764) dominate with strong correlations and Component 2 has Temperature (T, 0.653) and RSP (0.657) are associated with this component.

Seasonal variations proved that variable correlations and their contributions to components change between the SWM and NEM seasons, reflecting seasonal influences on environmental conditions. Study area variability proved thar different study areas exhibit unique patterns of variable clustering into components, indicating spatial variability in environmental dynamics. Strong Loadings consists of Temperature, RH, and CO2 frequently contribute to the first component, highlighting their fundamental influence on environmental variability. Rotation iterations showed the number of iterations (3 or 5) reflects the complexity of the data and convergence process.

Table 4.12 Rotated Component Matrix

SK TANJUNG GELAM (S1) [b]						
	SWM			NEM		
	Component			Component		
	1	2	3	1	2	3
T	-.840			.841		
RH	.822			-.625		
AM	.362			.553		
CO_2	.610			-.702		
CO		.775			.514	
HCHO		.642			.874	
RSP		.680				.831
TMG (S2) [b]						
	SWM			NEM		
	Component			Component		

	1	2	3	1	2	3
T	-.891					.682
RH	.776					.843
AM	.684					.733
CO_2	-.762					.660
HCHO		.603			.769	
RSP			.878	.585		
MSET (S3) [a]						
	SWM			NEM		
	Component			Component		
	1	2	3	1	2	3
T	.979			-.916		
RH	-.974			.893		
AM	.884			-.771		
CO_2	.845			.666		
HCHO		.862			.648	
TVOC		.831				
RSP			-.643		.987	
RAIA HOTEL (S4) [a]						
	SWM`			NEM		
	1	2		1	2	
T		.571		0.653		
RH		.762		0.752		
AM		.562		0.698		
RSP	.705				0.657	
CO_2		-.803		0.764		

Extraction Method: Principal Component Analysis.
Rotation Method: Varimax with Kaiser Normalization.
a. Rotation converged in 3 iterations.
b. Rotation converged in 5 iterations.

4.1.4 Prediction of Indoor Air Quality and Sick Building Syndrome

This study used inferential statistics to analyse the normality of the data. Assuming a 95% confidence level, if $p < 0.05$, the null hypothesis (H_o) is rejected, and it is concluded that the distribution is not normal. The normality test was performed by applying the Kolmogorov-Smirnov method. Equation 4.1 showed that the hypothesis was defined to determine the normality of the data set and considered as an overview of the variation in air pollutant concentration. This result should be verified and investigated further using statistical analysis of inferential statistics widely used in air pollution studies, such as Analysis of Variance (ANOVA). ANOVA was conducted to determine whether a statistically significant difference exists in the air pollutant concentration among the stations. The one-way ANOVA was anticipated, in which air pollutants were compared with a single factor (Station).

$$Ho: Data\ is\ normally\ distributed \tag{4.1}$$
$$H_1: Data\ is\ normally\ distributed$$

The results revealed that the p-value was 0.000 ($p < 0.05$) as presented in Table 4.13. Therefore, it rejects H_o. Thus, it rejects H_o. Therefore, the data was not normally distributed, and the results are the same for SBSS results in Table 4.14. In various areas of empirical studies, researchers are often interested in testing the homogeneity of distributions across different samples. The normality test was performed by applying the Kolmogorov-Smirnov method. This test was used to determine whether two distributions differ or whether an underlying probability distribution differs from a hypothesised distribution. It is used when we have two samples from two populations that can be different. Thus, the data proved that it was not normally distributed.

Table 4.13 Tests of normality for physical, chemical and ventilation performance indicators

	Kolmogorov-Smirnov		
S1	Statistic	df	Sig.
Standardised Residual for T	.251	720	.000
Standardized Residual for RH	.340	720	.000
Standardized Residual for AM	.484	720	0.000
Standardized Residual for CO_2	.138	720	.000
Standardized Residual for CO	.273	720	.000
Standardized Residual for HCHO	.226	720	.000
Standardized Residual for RSP	.253	720	.000
S2			
Standardized Residual for T	.448	595	0.000
Standardized Residual for RH	.289	595	.000
Standardized Residual for AM	.437	595	0.000
Standardized Residual for CO_2	.052	595	.001
Standardized Residual for HCHO	.268	595	.000
Standardized Residual for RSP	.109	595	.000
S3			
Standardized Residual for T	.083	392	.000
Standardized Residual for RH	.061	392	.001
Standardized Residual for AM	.184	392	.000
Standardized Residual for CO_2	.306	392	.000
Standardized Residual for TVOC	.495	392	.000
Standardized Residual for HCHO	.306	392	.000
Standardized Residual for RSP	.471	392	.000
S4			
Standardized Residual for T	.083	157	.011
Standardized Residual for RH	.117	157	.000
Standardized Residual for AM	.138	157	.000
Standardized Residual for CO_2	.346	157	.000
Standardized Residual for RSP	.128	157	.000

Table 4.14 Tests of normality for Sick Building Syndrome (SBS) symptoms

	Kolmogorov-Smirnov[a]		
	Statistic	df	Sig.
Standardized Residual for Headache	.387	22	.000
Standardized Residual for Feeling heavy-headed	.227	22	.004
Standardized Residual for Fatigue lethargy	.318	22	.000
Standardized Residual for Drowsiness	.349	22	.000
Standardized Residual for Dizziness	.452	22	.000
Standardized Residual for Nausea and vomiting	.437	22	.000
Standardized Residual for Cough	.318	22	.000
Standardized Residual for Hoarse, dry throat	.280	22	.000
Standardized Residual for Skin rash, itchiness	.283	22	.000
Standardized Residual for Irritation of the eye	.232	22	.003
S2			
Standardized Residual for Headache	.338	66	.000
Standardized Residual for Feeling heavy-headed	.270	66	.000
Standardized Residual for Fatigue lethargy	.244	66	.000
Standardized Residual for Drowsiness	.327	66	.000
Standardized Residual for Dizziness	.267	66	.000
Standardized Residual for Nausea and vomiting	.511	66	.000
Standardized Residual for Cough	.211	66	.000
Standardized Residual for Irritated, stuffy nose	.271	66	.000
Standardized Residual for Hoarse, dry throat	.181	66	.000
Standardized Residual for Skin rash, itchiness	.288	66	.000
Standardized Residual for Irritation of the eye	.307	66	.000
S3			
Standardized Residual for Headache	.357	32	.000
Standardized Residual for Feeling heavy-headed	.370	32	.000
Standardized Residual for Fatigue lethargy	.375	32	.000
Standardized Residual for Drowsiness	.402	32	.000
Standardized Residual for Dizziness	.402	32	.000
Standardized Residual for Nausea and vomiting	.370	32	.000
Standardized Residual for Cough	.402	32	.000
Standardized Residual for Irritated, stuffy nose	.331	32	.000
Standardized Residual for Hoarse, dry throat	.240	32	.000
Standardized Residual for Skin rash, itchiness	.302	32	.000
Standardized Residual for Irritation of the eye	.338	32	.000
S4			
Standardized Residual for Headache	.329	36	.000
Standardized Residual for Feeling heavy-headed	.190	36	.002
Standardized Residual for Fatigue lethargy	.266	36	.000
Standardized Residual for Drowsiness	.269	36	.000
Standardized Residual for Dizziness	.358	36	.000
Standardized Residual for Nausea and vomiting	.355	36	.000
Standardized Residual for Cough	.367	36	.000
Standardized Residual for Irritated, stuffy nose	.250	36	.000
Standardized Residual for Hoarse, dry throat	.237	36	.000
Standardized Residual for Skin rash, itchiness	.244	36	.000
Standardized Residual for Irritation of the eye	.173	36	.008

The study proceeds with checking the second assumption of ANOVA. The hypothesis was defined to test co-variance in the data set.

$$H_O: Data\ has\ equal\ variance \qquad (4.2)$$
$$H_1: Data\ has\ no\ equal\ variances$$

The co-variance was conducted by applying Levene's Test. The results revealed that the p-value was 0.000 (<0.005) (Table 4.15) at specific parameters. Therefore, H_o is rejected for physical, chemical, and performance indicators. Both normality and co-variance tests revealed that this dataset fails to meet parametric characteristics, and non-parametric tests are needed to determine the statistically significant difference in air pollutants. However, the results were inversely for building syndrome (SBS) symptoms (Table 4.16), meaning the co-variances are insignificant at each SBS symptoms =. Kruskal Wallis test was often used for the non-parametric test. Kruskal–Wallis test is a non-parametric statistical test that evaluates whether two or more samples are drawn from the same distribution.

Table 4.15 Levene's test of equality of error variances for physical, chemical and ventilation performance indicators

S1	F	df1	df2	Sig.
T	202.697	1	645	.000
RH	10.440	1	645	.001
AM	3.689	1	645	.055
CO_2	12.583	1	645	.000
CO	120.554	1	645	.000
HCHO	341.897	1	645	.000
RSP	17.205	1	645	.000
S2	F	df1	df2	Sig.
T	1.430	1	720	.032
RH	1.971	1	720	.006
AM	2.529	1	720	.112
CO_2	.928	1	720	.336
HCHO	81.042	1	720	.000
RSP	5.240	1	720	.022
S3	F	df1	df2	Sig.
T	2.330	1	540	.128
RH	5.726	1	540	.017
AM	.026	1	540	.008
CO_2	1.510	1	540	.220
TVOC	302.768	1	540	.000
HCHO	47.741	1	540	.000

	F	df1	df2	Sig.
RSP	.120	1	540	.030
S4	F	df1	df2	Sig.
T	1.659	1	960	0.002
RH	0.597	1	960	0.041
AM	0.806	1	960	0.001
CO_2	0.068	1	960	0.094
RSP	0.713	1	960	0.054

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a Design: Intercept + MONSOON

Table 4.16 Levene's test of equality of error variances for Sick Building Syndrome Symptoms (SBSS)

S1	F	df1	df2	Sig.
Headache	0.000	1	20	0.010
Feeling heavy headed	0.000	1	20	1.000
Fatigue lethargy	0.000	1	20	1.000
Drowsiness	0.000	1	20	0.024
Dizziness	0.000	1	20	1.000
Nausea vomiting	0.000	1	20	1.000
Cough	0.000	1	20	1.000
Irritated stuffy nose		1	20	0.034
Hoarse dry throat	0.000	1	20	1.000
Skin rash itchiness	0.000	1	20	1.000
Irritation of the eye	0.000	1	20	1.000
S2	F	df1	df2	Sig.
Headache	0.000	1	64	1.000
Feeling heavy headed	0.000	1	64	1.000
Fatigue lethargy	0.000	1	64	1.000
Drowsiness	.002	1	64	.968
Dizziness	0.000	1	64	1.000
Nausea vomiting	0.000	1	64	1.000
Cough	.281	1	64	.598
Irritated stuffy nose	.438	1	64	.010
Hoarse dry throat	.039	1	64	.845
Skin rash itchiness	0.000	1	64	1.000
Irritation of the eye	0.000	1	64	0.021
S3	F	df1	df2	Sig.
Headache	0.000	1	30	1.000
Feeling heavy headed	0.000	1	30	1.000
Fatigue lethargy	0.000	1	30	1.000
Drowsiness	0.000	1	30	0005
Dizziness	0.000	1	30	0.025
Nausea vomiting	0.000	1	30	1.000
Cough	0.000	1	30	0.032
Irritated stuffy nose	0.000	1	30	1.000
Hoarse dry throat	0.000	1	30	1.000
Skin rash itchiness	0.000	1	30	1.000
Irritation of the eye	0.000	1	30	1.000
S4	F	df1	df2	Sig.
Headache	.089	1	34	.767
Feeling heavy headed	.002	1	34	.966

Fatigue lethargy	1.735	1	34	.197
Drowsiness	4.389	1	34	.044
Dizziness	3.415	1	34	.073
Nausea vomiting	18.350	1	34	.000
Cough	0.000	1	34	1.000
Irritated stuffy nose	2.176	1	34	.049
Hoarse dry throat	2.569	1	34	.018
Skin rash itchiness	.425	1	34	.519
Irritation of the eye	.246	1	34	.623

Tests the null hypothesis that the error variance of the dependent variable is equal across groups.
a. Design: Intercept + Monsoon

Like ANOVA, the Kruskal-Wallis test compares two or more samples, focusing on cases with three or more samples. The H_o of the Kruskal Wallis was different from those of ANOVA. For ANOVA, the H_o was all the means of the populations from which the samples are drawn are the same; the alternative hypothesis (H_1) implies that at least two of these means are different from each other). The hypothesis was defined as in equation 4.3.

$$H_o: \mu s_1 = \mu s_2 = \mu s_3 = \mu s_4 \text{ (no mean difference for the 4 sites)} \quad (4.3)$$

$$H1: \mu s1 \neq \mu s2 \neq \mu s3 \neq \mu s4$$

Table 4.17 shows that the Kruskal Wallis Test displayed a p-value with a statistically significant difference, less than 0.005 ($p<0.05$). Thus, H_o is rejected. This value showed that air pollutant concentration has a statistically significant difference. Further analysis was performed to simultaneously compare air pollutant concentration between each site [N=645 (S1); N=720 (S2); N=540 (S3); N=960 (S4) (one station; each parameter); $N_{\text{all station; all parameters}}$ = 19560].

Table 4.17 Kruskal Wallis Test

S1	T	RH	AM	CO_2	CO	TVOC	HCHO	RSP
Chi-Square	204.336	67.415	61.103	126.975	17.425	-	249.897	59.704
df	1	1	1	1	1	-	1	1
Asymp. Sig.	.000	.000	.000	.000	.000	-	.000	.000
S2	T	RH	AM	CO_2	CO	TVOC	HCHO	RSP
Chi-Square	226.804	3.211	8.672	39.345	-	-	3.223	63.998
df	1	1	1	1	-	-	1	1
Asymp. Sig.	.000	.073	.003	.000	-	-	.073	.000
S3	T	RH	AM	CO_2	CO	TVOC	HCHO	RSP
Chi-Square	9.777	1.752	4.686	46.958	163.953	345.744	4.266	.765
df	1	1	1	1	1	1	1	1
Asymp. Sig.	.002	.186	.030	.000	.000	.000	.039	.382
S4	T	RH	AM	CO_2	CO	TVOC	HCHO	RSP
Chi-Square	12.893	.188	.228	17.581	-	-	3.336	71.457
df	1	1	1	1	-	-	1	1
Asymp. Sig.	.000	.664	.633	.000	-	-	.068	.000

There exist statistically significant differences in physical-chemical parameters and ventilation performance indicators at all sites. Multiple comparisons were conducted to simultaneously examine the physical-chemical parameters and ventilation performance indicator concentration at all sites. Tables 4.18 and 4.19 displayed results from multiple comparisons of physical and chemical parameters and performance ventilation indicators concentration among sites. Multiple comparisons revealed that there exist significant differences in temperature concentrations between S1 and S2, S1 and S3, S1 and 4, S2 and S1, S3 and S1, S3 and S4, S4 and S1, and S4 and S3 (Table 4.18 (a)). Relative humidity (RH) (Table 4.18 (c)) at each study area also exists significantly different between S1 and S2, S1 and S4, S2 and S1, S2 and S4, S3 and S2, S3 and S4, S4 and S1, S4 and S2, and S4 and S3. Ventilation performance indicators which carbon dioxide (CO_2) in each study area also have some significant differences, which are shown in Table 4.18 (b), S1 and S2, S1 and S3, S1 and S4, S2 and S1, S2 and S3, S2 and S4, S3 and S1, S3 and S2, S3 and S4, S4 and S1, S4 and S2, and S4 and S3. This multiple comparison revealed that there exist significant differences for formaldehyde (HCHO), Table 4.18 (d) concentrations between S1 and S3, S2 and S3, S3 and S1, S3 and S1, S3 and S2, S3 and S4, and S4 and S3. Total volatile organic compound (TVOC), Table 4.18 (e) also showed a few significant between S1 and S3 and S3 and S1, in which both study areas were open ventilation. This might be due to the site specification, which in turn resulted in different temperature concentration levels which can be caused by geographical area, meteorological factors, traffic-generated air pollutants, including physical activities, and different sources of emission from different industrial activities that can influence the temperature in the study areas.

Table 4.18 Multiple Comparisons

a) Dependent Variable: Temperature
Tukey HSD

(I) SITE		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1	2	20.682*	3.799	0.000	10.915	30.449
	3	14.927*	3.578	0.000	5.730	24.124
	4	26.093*	3.752	0.000	16.448	35.738
2	1	-20.682*	3.799	0.000	-30.449	-10.9148
	3	-5.755	3.715	0.408	-15.306	3.796
	4	5.412	3.883	0.503	-4.571	15.395
3	1	-14.927*	3.578	0.000	-24.124	-5.730
	2	5.755	3.715	0.408	-3.796	15.306
	4	11.166*	3.667	0.013	1.740	20.592
4	1	-26.093*	3.752	0.000	-35.738	-16.448
	2	-5.412	3.883	0.503	-15.395	4.5710
	3	-11.166*	3.667	0.013	-20.592	-1.740

Based on observed means.
The error term is Mean Square (Error) = 4593.398.

b) Dependent Variable: CO_2
Tukey HSD

(I) SITE		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1	2	-147.219*	8.119	0.000	-168.090	-126.348
	3	88.955*	7.645	0.000	69.302	108.607
	4	-172.010*	8.017	0.000	-192.620	-151.400
2	1	147.219*	8.119	0.000	126.348	168.090
	3	236.174*	7.939	0.000	215.764	256.583
	4	-24.791*	8.298	0.015	-46.124	-3.458
3	1	-88.955*	7.645	0.000	-108.607	-69.302
	2	-236.174*	7.939	0.000	-256.583	-215.764
	4	-260.965*	7.835	0.000	-281.107	-240.822
4	1	172.010*	8.017	0.000	151.400	192.620
	2	24.791*	8.299	0.015	3.458	46.124
	3	260.965*	7.835	0.000	240.822	281.107

Based on observed means.
The error term is Mean Square(Error) = 20974.706.

c) Dependent Variable: RH
Tukey HSD

(I) SITE		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1	2	13.292*	1.567	0.000	9.265	17.320
	3	2.257	1.475	0.420	-1.536	6.049
	4	7.519*	1.547	0.000	3.542	11.497
2	1	-13.293*	1.567	0.000	-17.320	-9.264
	3	-11.036*	1.532	0.000	-14.975	-7.09
	4	-5.773*	1.601	0.002	-9.889	-1.656
3	1	-2.257	1.475	0.420	-6.049	1.5362
	2	11.036*	1.532	0.000	7.097	14.975

	4	5.263*	1.512	0.003	1.3756	9.150
4	1	-7.519*	1.547	0.000	-11.497	-3.542
	2	5.773*	1.602	0.002	1.656	9.889
	3	-5.263*	1.512	0.003	-9.150	-1.376

Based on observed means.
The error term is Mean Square(Error) = 781.238.

d) Dependent Variable: Formaldehyde
Tukey HSD

(I) SITE		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1	2	-0.002	.002	.790	-0.007	0.003
	3	-0.016*	.002	.000	-0.021	-0.011
	4	0.001	.003	.994	-0.007	0.009
2	1	0.002	.002	.790	-0.003	0.007
	3	-0.014*	.002	.000	-0.019	-0.009
	4	0.003	.003	.832	-0.005	0.011
3	1	0.016*	.002	.000	0.011	0.021
	2	0.014*	.002	.000	0.009	0.019
	4	0.017*	.003	.000	0.008	0.025
4	1	-0.001	.003	.994	-0.009	0.007
	2	-0.003	.003	.832	-0.011	0.005
	3	-0.017*	.003	.000	-0.025	-0.008

Based on observed means.
The error term is Mean Square(Error) = .001.

e) Dependent Variable: TVOC
Tukey HSD

(I) SITE		Mean Difference (I-J)	Std. Error	Sig.	95% Confidence Interval Lower Bound	Upper Bound
1	3	-1.238*	0.134	.000	-1.552	-.9242
	4	0.041	1.144	.999	-2.644	2.726
3	1	1.238*	.1338	.000	0.924	1.552
	4	1.279	1.145	.504	-1.408	3.967
4	1	-.0413	1.144	.999	-2.726	2.644
	3	-1.279	1.145	.504	-3.967	1.408

Based on observed means.
The error term is Mean Square(Error) = 5.207.
*. The mean difference is significant at the 0.05 level.

Table 4.19 Summarisation of multiple comparisons

Site			**P-value**	**Conclusion**
Temp				
1	versus	2	0.000*	Significantly different
1	versus	3	0.000*	Significantly different
1	versus	4	0.000*	Significantly different
2	versus	3	0.000*	Significantly different
2	versus	4	0.000*	Significantly different
3	versus	4	0.013*	Significantly different
RH				
1	versus	2	0.000*	Significantly different
1	versus	3	0.000*	Significantly different

1	versus	4	0.000*	Significantly different
2	versus	3	0.002*	Significantly different
2	versus	4	0.000*	Significantly different
3	versus	4	0.003*	Significantly different
CO_2				
1	versus	2	0.000*	Significantly different
1	versus	3	0.000*	Significantly different
1	versus	4	0.000*	Significantly different
2	versus	3	0.000*	Significantly different
4	versus	2	0.015*	Significantly different
4	versus	3	0.000*	Significantly different
HCHO				
1	versus	3	0.000*	Significantly different
2	versus	3	0.000*	Significantly different
2	versus	1	0.000*	Significantly different
TVOC				
1	versus	3	0.000*	Significantly different
3	versus	1	0.000*	Significantly different

Statistical significance: *p<0.05

4.1.5 Model Development

Table 4.20 shows a resume of the statistical model results performance for two models (SWM and NEM) for each dependent variable in S1. The first column of Table 4.20 presents the statistics test most often used in generalized linear models and represents measures of dispersion (generalized and corrected), which permit testing the quality of models. Values from Table 4.20 confirm that model NEM (headache, feeling heavy-headed, fatigue or lethargy, dizziness and skin rashness) has the best performance results, as shown by the statistical tests. These statistical tests are obtained using all the deviations between the estimated and recorded (residuals) for each observation. Considering the Akaike Information Criterion, the objective is to minimize AIC. Model NEM (headache, feeling heavy-headed, fatigue or lethargy, dizziness and skin rashness) has the lowest AIC of the two models, which means that the evidence for model NEM (headache, feeling heavy-headed, fatigue or lethargy, dizziness and skin rashness) is the best due to NEM having lowest AIC value than SWM. When comparing 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 two are suitable. The SWM model (drowsiness, cough, hoarse and dry throat and eye irritation) is considered the best, and each model has a more significant explanation of the dependent variable using some explanatory variables than any other model without explanatory variables. Table 4.21 shows the likelihood ratio chi-square test, which compares each model with the null model.

Table 4.20 Goodness of Fit[a] (S1)

	SWM			NEM		
	Value	df	Value/df	Value	df	Value/df
Headache						
Deviance	.478	6	.080	.098	6	.016
Scaled Deviance	11.079	6		11.016	6	
Log Likelihood	-6.140			**-2.578**		
Akaike's Information Criterion (AIC)	24.281			**6.843**		
Finite Sample Corrected AIC (AICC)	45.281			**27.843**		
Feeling Heavy Headache						
Deviance	1.115	6	.186	.875	5	.175
Scaled Deviance	11.183	6		11.144	5	
Log Likelihood	-9.874			**-8.521**		
Akaike's Information Criterion (AIC)	31.748			**31.042**		
Finite Sample Corrected AIC (AICC)	52.748			**48.375**		
Fatigue Or Lethargy						
Deviance	1.063	7	.152	.371	5	.074
Scaled Deviance	11.174	7		11.062	5	
Log Likelihood	-9.893			**-4.049**		
Akaike's Information Criterion (AIC)	29.785			**22.098**		
Finite Sample Corrected AIC (AICC)	41.785			**39.431**		
Drowsiness						
Deviance	.613	7	.088	.583	5	.117
Scaled Deviance	11.101	7		11.096	5	
Log Likelihood	**-7.925**			-7.649		
Akaike's Information Criterion (AIC)	**25.850**			29.298		
Finite Sample Corrected AIC (AICC)	**37.850**			66.632		
Dizziness						
Deviance	.524	7	.075	.004	6	.001
Scaled Deviance	11.087	7		11.001	6	
Log Likelihood	-.989			**-.2600**		
Akaike's Information Criterion (AIC)	11.977			**-40.001**		
Finite Sample Corrected AIC (AICC)	23.977			**-19.001**		
Nausea and vomiting						
Deviance	.223	6	.037	.073	5	.015
Scaled Deviance	11.037	6		11.012	5	
Log Likelihood	4.363			**1.759**		
Akaike's Information Criterion (AIC)	20.726			**10.481**		
Finite Sample Corrected AIC (AICC)	47.726			**42.814**		
Cough						
Deviance	.396	7	.057	.642	8	.080
Scaled Deviance	11.066	7		11.106	8	
Log Likelihood	**-4.411**			-7.082		
Akaike's Information Criterion (AIC)	**18.821**			22.164		
Finite Sample Corrected AIC (AICC)	**20.821**			28.831		
Hoarse Or Dry Throat						

Deviance	1.308	7	.187	1.150	7	.164
Scaled Deviance	11.214	7		11.188	7	
Log Likelihood	**-10.738**			-11.458		
Akaike's Information Criterion (AIC)	**31.476**			32.916		
Finite Sample Corrected AIC (AICC)	**43.476**			44.916		
Skin Rash or Itchiness						
Deviance	1.477	7	.211	1.199	7	.171
Scaled Deviance	11.241	7		11.196	7	
Log Likelihood	-12.954			**-11.785**		
Akaike's Information Criterion (AIC)	35.908			**33.569**		
Finite Sample Corrected AIC (AICC)	47.908			**45.569**		
Irritation of Eye						
Deviance	1.596	6	.266	1.454	7	.208
Scaled Deviance	11.259	6		11.237	7	
Log Likelihood	**-11.766**			-12.290		
Akaike's Information Criterion (AIC)	**33.533**			36.580		
Finite Sample Corrected AIC (AICC)	**45.533**			57.580		

Model SWM (drowsiness, cough, hoarse or dry throat) has the lowest AIC, which means that evidence for the model SWM (drowsiness, cough, hoarse or dry throat) is the best. Regardless of the model, SWM (drowsiness, cough, hoarse or dry throat and irritation of eyes) is considered the best; each model, individually, has a more significant explanation of the dependent variable using some of the explanatory than any other model without explanatory variables. Table 4.21 shows the likelihood ratio chi-square test, which compares each model with the null model. Regardless of model SWM (drowsiness, cough, hoarse or dry throat) is considered the best due to the highest value compared to model NEM (drowsiness, cough, hoarse or dry throat), each model individually has a more significant explanation of the dependent variable using some of the explanatory than any other model without explanatory variables.

Table 4.21Omnibus Test[a] (S1)

	Likelihood Ratio Chi-Square	df	Sig.
Headache			
SWM	22.328	6	.009
NEM	**24.890**	6	.000
Feeling Heavy Headache			
SWM	4.904	4	.007
NEM	**8.609**	5	.001
Fatigue Or Lethargy			
SWM	0.888	3	.038
NEM	**0.975**	5	.028

Drowsiness			
SWM	**5.869**	3	.027
NEM	4.421	5	.040
Dizziness			
SWM	8.716	3	.033
NEM	**9.694**	4	.000
Nausea and vomiting			
SWM	16.363	4	.003
NEM	**25.608**	5	.000
Cough			
SWM	**16.851**	3	.008
NEM	11.509	2	.039
Hoarse Or Dry Throat			
SWM	**2.086**	3	.014
NEM	1.525	3	.016
Skin Rash or Itchiness			
SWM	2.395	3	.041
NEM	**10.734**	3	.034
Irritation of Eye			
SWM	1.925	4	.044
NEM	**2.972**	3	.036

Table 4.22 shows the equation of S1 to determine the influence of IAQ towards SBSS. Two models for each symptom consist of SWM and NEM. Headache was decreased by 0.207 units when temperature variables went up by one unit, 0.026 unit in Headache decreasing one unit of RH, 0.099 unit for Headache caused the decrease in one unit of air movement and, increasing 0.02-unit Headache when CO_2 increase by one unit in exponential term which showed equation (4.4) for model SWM.

Equation (4.5) showed that feeling heavy-headed increased by 0.071 units when RH increased by one unit. Feeling heavy-headed was decreased by 0.585 units when one unit of AM. Increasing the 0.001 unit of feeling heavy-headed when CO2 increases by one unit and increasing the 0.01 unit of feeling heavy-headed caused an increase in one unit of formaldehyde in exponential terms, shown in the SWM model in exponential terms.

Decreasing 0.012 unit of fatigue or lethargy caused by increasing one unit of RH, increasing 0.803 unit feeling heavy headed when increasing one unit of AM, and increasing one unit of 0.001 fatigue or lethargy caused by increasing one unit of CO_2 in exponential term which showed in equation (4.6)

Drowsiness was decreased by 0.394 units when air movement (AM) variables went up by one unit, 0.002 unit in Drowsiness decreasing one unit of CO_2, and 0.124 unit for Headache caused the decrease in one unit of temperature (T), which showed equation (4.7) in the exponential term.

Equation (4.8), decreasing 0.283-unit Dizziness increased by one unit of T, decrease 0.225 unit of Dizziness increase one unit of AM and increase one unit of CO. Equation (4.9), increase 0.006 unit of nausea or vomiting caused by decreasing one unit of CO_2, increase 0.027 unit of nausea or and vomiting due to decrease one unit of CO, increase 0.139 unit of nausea or and vomiting increase one unit of T and increase 0.064 unit of nausea or vomit by increase one unit of RH in exponential term.

Equation (4.10) shows an increase of 0.240 units and 0.004 units of cough caused by the rise of one unit of T and CO_2 and an increase of 0.055 units of cough caused by the rise of one unit of CO in exponential terms.

Equation (4.11) shows an increase of 0.202 units of hoarse or dry throat due to the rise of one unit of T and a decrease of 0.035 units and 0.047 units of hoarse or dry throat by decreasing T and CO_2 exponentially.

Equation (4.12) shows an increase of 0.069 units and 0.010 units of skin rash and itchiness due to increased T and CO and a decrease of 0.288 units of skin rash and itchiness caused by increased one unit of AM in the exponential term.

Equations (4.13), 0.222-, 0.295- and 0.001-unit irritation of the eye decrease one unit of T, HCHO and CO_2 and increase 0.034-unit eye irritation caused by an increase of one unit of CO in the exponential term.

Equation (4.14), Headache increases by 0.208 units, 0.006 units and 0.706 units due to the rise of one unit of T, CO_2 and RSP, a decrease of 0.603 units of headache increase of one unit of AM in the exponential term.

Equation (4.15), Feeling heavy-headed increases by 0.223 units and 0.055 units when there is an increase of one unit of T and HCHO, decreases by 0.025-unit, 0.990 unit and 0.007 unit of feeling heavy-headed when there is an increase one unit of T, AM and CO_2 in the exponential term.

Equation (4.16), Fatigue and lethargy increase by 0.113 units, 0.426 units and 0.812 units when increasing one unit of T, AM and HCHO, decrease by 0.032-unit, 0.005 unit when increasing one unit of RH, and CO_2 in the exponential term.

Equation (4.17), Drowsiness increases by 0.025 units and 0.023 units when one unit of T and RH decreases by 0.580 units and 0.048 units when one unit of AM and HCHO in the exponential term.

Equation (4.18), Dizziness increases 0.135-unit, 0.009 unit and 6.252e-0.005 unit when one unit of T, RH and CO_2 decreases 0.489 unit increases one unit of AM in exponential term.

Equation (4.19) m Nausea or vomiting increases 0.202 units when going up one unit of RH, decreases 0.050 unit,0.615-unit, 0.033 unit, and 0.342 unit can increase one unit of T, CO, HCHO and RSP in the exponential term.

Equation (4.20) Cough increases by 0.078 units and 5.842 units when increasing one unit of CO and AM exponentially.

Equation (4.21) Hoarse or dry throat increases by 0.211 units and 0.034 units when one unit of T and RH decreases by 0.0.56 units and 0.182 units when increasing one unit of AM and TVOC in exponential terms.

Equation (4.22) Skin rash and itchiness increase by 0.19 units and 0.119 units when one unit of AM and T increase, decrease 0.922 units of skin rash and itchiness increase by one unit of RSP in the exponential term.

Equation (4.23), Irritation of the eye increases by 0.903 units and 0.045 units when one unit of AM and RH increases by 0.659 units when increasing one unit of RSP in exponential terms.

Table 4.22 Equation of SK Tanjung Gelam (S1)

SOUTHWEST MONSOON

$$In\ Headache = 7.958 - 0.207T - 0.026RH - 0.099AM + 0.02CO_2 \quad (4.4)$$

$$In\ Feeling\ Heavy\ Headed = 0.071\ RH - 0.585AM + 0.001CO_2 + 0.01\ HCHO \quad (4.5)$$

$$In\ Fatigue\ or\ Lethergy = 1.217 - 0.012\ RH + 0.803AM + 0.001CO_2 \quad (4.6)$$

$$In\ Drowsiness = 5.213 - 0.394AM - 0.002CO_2 - 0.124\ T \quad (4.7)$$

$$In\ Dizziness = 7.892 - 0.283T - 0.225AM + 0.066CO \quad (4.8)$$

$$In\ Nausea\ or\ vomitting = 0.139T - 0.006CO_2 - 0.027\ CO + 0.064RH - 5.752 \quad (4.9)$$

$$In\ Cough = 8.955 - 0.240T - 0.004CO_2 + 0.055CO \quad (4.10)$$

$$In\ Hoarse\ or\ dry\ throat = 1.887 - 0.035T - 0.000472CO_2 + 0.202RSP \quad (4.11)$$

$$In\ Skin\ rash\ or\ itchiness = 0.069T - 0.288AM + 0.010CO - 1.051 \quad (4.12)$$

$$In\ Irritation\ of\ eye = 7.379 - 0.222T - 0.295HCHO + 0.034CO - 0.001CO_2 \quad (4.13)$$

NORTHEAST MONSOON

$$In\ Headache = 0.208T - 0.603AM + 0.006CO_2 + 0.706\ RSP - 2.274 \quad (4.14)$$

$$In\ Feeling\ heavy\ headed = 0.223T - 0.025RH - 0.990AM + 0.055HCHO - 0.007CO_2 - 2.155 \quad (4.15)$$

$$In\ Fatigue\ or\ lethargy = 0.221 + 0.113T - 0.032RH + 0.426AM + 0.812HCHO - 0.005CO_2 \quad (4.16)$$

$$In\ Drowsiness = 0.025T + 0.023RH - 0.580AM - 0.048HCHO - 1.610 \quad (4.17)$$

$$In\ Dizziness = 0.135T + 0.009RH - 0.489AM + (6.252 \times 10^{-5})CO_2 \quad (4.18)$$

$$In\ Nausea\ or\ vomiting = 0.202RH - 0.050T - 0.615CO - 0.033HCHO - 0.342RSP - 8.509 \quad (4.19)$$

$$In\ Cough = 0.078CO + 5.842AM - 0.190 \quad (4.20)$$

$$In\ Hoarse\ or\ dry\ throat = 1.523 + 0.211T - 0.056AM + 0.034RH - 0.182TVOC \quad (4.21)$$

$$In\ Skin\ rash\ or\ itchiness = 0.191AM + 0.119T - 0.922RSP - 2.781 \quad (4.22)$$

$$In\ Irritation\ of\ eye = 0.903AM - 0.659RSP + 0.045RH - 2.633 \quad (4.23)$$

Table 4.23 shows the two models for S2. Model NEM (headache, fatigue or lethargy, drowsiness, dizziness, hoarse or dry throat, skin rash or itchiness and eye irritation) has the lowest AIC. The value of AIC was 68.957 for NEM compared to the AIC value at SWM, which was 72.506 for headache, as shown in Table 4.23. This showed that the NEM AIC value for headache is smaller than SWM. The same can be concluded when analysing AICC (Akaike Information Criterion corrected by minimising the number of model parameters). When comparing 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 two are suitable. Regardless of the model, SWM (feeling heavy-headed, nausea or vomiting, and cough) is considered the best; each model, individually, has a more significant explanation of the dependent variable using some of the explanatory than any other model without explanatory variables. Table 4.24 shows the likelihood ratio chi-square test, which compares each model with the null model. Regardless of model NEM (headache, fatigue or lethargy, drowsiness, dizziness, hoarse or dry throat, skin rash or itchiness and eye irritation) is considered the best due to the highest value compared to model SWM (feeling heavy-headed, nausea or vomiting, and cough), each model individually, has a more significant explanation of the dependent variable using some of the explanatory than any other model without explanatory variables.

Table 4.23 Goodness of Fit (S2)

	SWM			NEM		
	Value	df	Value/df	Value	df	Value/df
Headache						
Deviance	3.544	27	.131	3.004	26	.116
Scaled Deviance	33.580	27		33.493	26	

Log Likelihood	-29.253			**-26.479**		
Akaike's Information Criterion (AIC)	72.506			**68.957**		
Finite Sample Corrected AIC (AICC)	76.986			**74.957**		
Feeling Heavy Headache						
Deviance	4.862	29	.168	4.462	26	.172
Scaled Deviance	33.790	29		33.726	26	
Log Likelihood	**-39.326**			-37.874		
Akaike's Information Criterion (AIC)	**88.653**			91.749		
Finite Sample Corrected AIC (AICC)	**90.875**			97.749		
Fatigue Or Lethargy						
Deviance	4.094	27	.152	3.425	27	.127
Scaled Deviance	33.668	27		33.561	27	
Log Likelihood	-33.705			**-30.706**		
Akaike's Information Criterion (AIC)	81.410			**75.412**		
Finite Sample Corrected AIC (AICC)	85.890			**79.892**		
Drowsiness						
Deviance	3.627	27	.134	3.135	27	.116
Scaled Deviance	33.593	27		33.514	27	
Log Likelihood	-29.641			**-25.693**		
Akaike's Information Criterion (AIC)	73.281			**65.386**		
Finite Sample Corrected AIC (AICC)	77.761			**69.866**		
Dizziness						
Deviance	2.704	27	.100	3.784	28	.135
Scaled Deviance	33.444	27		33.618	28	
Log Likelihood	**-28.537**			-34.174		
Akaike's Information Criterion (AIC)	**71.073**			80.349		
Finite Sample Corrected AIC (AICC)	**75.553**			83.579		
Nausea and vomiting						
Deviance	1.656	27	.061	1.694	28	.060
Scaled Deviance	33.274	27		33.280	28	
Log Likelihood	-17.001			**-17.375**		
Akaike's Information Criterion (AIC)	48.002			**46.750**		
Finite Sample Corrected AIC (AICC)	52.482			**49.980**		
Cough						
Deviance	2.231	28	.080	2.965	27	.110
Scaled Deviance	33.368	28		33.487	27	
Log Likelihood	**-30.531**			-30.775		
Akaike's Information Criterion (AIC)	**73.061**			75.551		
Finite Sample Corrected AIC (AICC)	**76.292**			80.031		
Hoarse Or Dry Throat						
Deviance	5.168	28	.185	4.583	27	.170
Scaled Deviance	33.838	28		33.746	27	
Log Likelihood	-37.349			**-32.311**		
Akaike's Information Criterion (AIC)	86.697			**78.622**		
Finite Sample Corrected AIC (AICC)	89.928			**83.102**		
Skin Rash or Itchiness						
Deviance	3.649	28	.130	3.061	28	.109
Scaled Deviance	33.597	28		33.502	28	
Log Likelihood	-31.651			**-28.705**		
Akaike's Information Criterion (AIC)	75.303			**69.410**		
Finite Sample Corrected AIC (AICC)	78.533			**72.641**		

Irritation of Eye						
Deviance	3.476	27	.129	2.966	28	.106
Scaled Deviance	33.569	27		33.487	28	
Log Likelihood	-30.431			**-27.772**		
Akaike's Information Criterion (AIC)	74.862			**67.545**		
Finite Sample Corrected AIC (AICC)	79.342			**70.775**		

The Omnibus test was conducted in Table 4.24. An omnibus test is a comprehensive test employed to ascertain whether there are any overall effects or differences in a model or set of variables. It is used as an initial screening instrument to evaluate a general hypothesis regarding a collection of variables. The results of an omnibus test frequently indicate a significant effect, but they do not provide specific information regarding its location. The simplest way to understand the omnibus test is to determine whether there are any significant differences or relationships in a dataset. Due to the data collected having two different datasets, which are for SWM and NEM, the likelihood ratio chi-squared was calculated and used in the context of model fitting, such as in regression models or structural equation modelling, to compare nested models.

Model SWM (feeling heavy-headed, dizziness, nausea or vomiting and coughing) has the lowest significance in Table 4.24, which shows the best significance when the likelihood ratio chi-square value is higher. The present symptoms of NEM include headache, fatigue or lethargy, drowsiness, hoarse or dry throat, skin rash or itchiness, and eye irritation.

Table 4.24 Omnibus Test[a] (S2)

	Likelihood Ratio Chi-Square	df	Sig.
Headache			
SWM	1.630	5	.045
NEM	**7.179**	6	.030
Feeling Heavy Headache			
SWM	**7.971**	3	.008
NEM	3.875	6	.046
Fatigue Or Lethargy			
SWM	11.253	5	.047
NEM	**15.256**	5	.038
Drowsiness			

SWM	3.258	5	.026
NEM	**9.854**	5	.017
Dizziness			
SWM	**13.903**	5	.016
NEM	2.628	4	.022
Nausea and vomiting			
SWM	**1.492**	5	.014
NEM	.744	4	.046
Cough			
SWM	**6.893**	5	.029
NEM	3.729	4	.044
Hoarse Or Dry Throat			
SWM	4.165	5	.026
NEM	**9.234**	4	.022
Skin Rash or Itchiness			
SWM	3.321	4	.056
NEM	**9.214**	4	.046
Irritation of Eye			
SWM	3.266	5	.050
NEM	**8.584**	4	.012

Table 4.25 shows the equation of S1 to determine the influence of IAQ towards SBS symptoms. Two models for each symptom consist of SWM and NEM. Equation (4.24) -(4.33) showed the equation for the southwest monsoon, and Equation (4.34) -(4.43) showed the equation for the northeast monsoon. Headache increased by 0.169 units and 0.067 units when one unit of AM and RH went up one unit, decreased by 0.18 units, 0.339 units and 0.162 units when one unit of T, CO2 and HCHO increased as shown in Equation (4.24).

Equation (4.25), Feeling heavy-headed increases by 0.2 units when one unit of AM, decreases by 0.554 units and 0.208 units when increasing one unit of T and CO_2.

Equation (4.26), Fatigue and lethargy increase by 0.346-unit, 0.059 unit and 0.008 units when increasing one unit of T, AM, and RH decrease by 0.476 unit, and 0.934 unit increase by one unit of CO_2 and RSP in the exponential term.

Equation (4.27), Drowsiness increases by 0.109 units, 0.744 units, and 0.085 units when one unit of AM, CO_2, and RH decreases by 0.233 units of drowsiness when increasing one unit of T in the exponential term.

Equation (4.28), Dizziness increases by 0.396 units, 0.354 units and 0.003 units when one unit of AM, RH and CO_2 increases. Decrease 0.537 units and 0.795 units of dizziness when increasing one unit of T and HCHO variables in the exponential term.

Equation (4.29) Nausea or vomiting increases by 0.168 units when one unit of CO increases and decreases by 0.237 units. 0.077 unit and 0.107 unit when increasing one unit of T, RH and HCHO in the exponential terms.

Equation (4.30), Cough increases by 0.655 units when one unit of RH increases, decreases 0.043 units, 0.101 units,0.462 units and 0.511 units when one unit of T, AM, CO2and RSP increases exponentially.

Equation (4.31), Hoarse or dry throat increases by 0.403 units, 0.293 units, and 1.272 units when one unit of AM, RH and CO2 increases, decreases 0.221 units of the hoarse or dry throat when increasing one unit of T in the exponential terms.

Equation (4.32), Skin rashness and itchiness increase by 1.158-unit, 0.461 units, 0.061 units and 0.458 units when one unit goes up for T, AM, HCHO and RSP, decrease by 0.147 unit of skin rashness and itchiness when one unit of RH decrease in exponential term.

In equation (4.33), eye irritation increases by 0.012 units, 0.394 units and 0.199 units when one unit of T, RH and AM increases and decreases by 0.013 unit of eye irritation when one unit of CO_2 increases exponentially.

Equation (4.34), Headache increases by 0.706 units when one unit of AM and CO_2 increase, decreases by 0.086 units, 0.174 units and 0.202 units when one unit increases T, HCHO and RSP in exponential terms.

Equation (4.35), Feeling heavy-headed increases 0.241-unit, 0.584-unit, 0.313 unit and 0.061 unit when one unit of RH, AM, CO_2 and RSP increase, decreases 0.403 unit of feeling headed increases one unit of T and HCHO in exponential term.

Equation (4.36): Fatigue and lethargy increase 0.402 units, 0.118 units, and 0.704 when one unit of RH, AM, and CO_2 is increased, and decrease 0.587 units and 0.013 units when one unit of T and RSP is increased in the exponential term.

Equation (4.37), Drowsiness increases by 0.193-unit, 0.031 unit and 0.115 units when increasing one unit of T, AM, and CO_2 decreases by 0.083 unit and 0.128 unit of drowsiness when increasing one unit of RH and RSP in the exponential term.

Equation (4.38): Dizziness increases by 0.091 units and 0.006 units when one unit of T and RH is increased and decreases by 0.034 units and 0.373 units when one unit of CO_2 and RSP is increased in the exponential term.

Equation (4.39): Nausea and vomiting increase by 0.028 units, 0.117 units, and 0.014 units when one unit of T, RH, and CO2 increases and decrease by 0.090 units when one unit of RSP is increased in the exponential term.

Equation (4.40): Cough increases by 0.293 units, 0.193 units, and 0.008 units when one unit of T, RH, and RSP is increased and decreases by 0.101 units when one unit of CO_2 is increased in the exponential term.

Equation (4.41), Hoarse or dry throat increases by 0.262 units and 0.257 units when increasing one unit of RH and CO_2, decreases by 0.257 units and 0.570 unit of the hoarse or dry throat when increasing one unit of T and RSP in the exponential term.

Equation (4.42), Skin rashness and itchiness increase by 0.635-unit, 0.770 units and 0.287 units when one unit of RH, CO_2 and RSP increases, decrease by 0.013 unit of skin rashness and itchiness when one unit of T in exponential term.

Equation (4.43), Irritation of the eye increases by 0.124-unit, 0.428 unit and 0.157 unit when one unit increases T, RH And RSP variables, decreases 0.441-unit eye irritation when one unit of CO_2 increases exponentially.

Table 4.25 Equation of TMG Mart (S2)

SOUTHWEST MONSOON

$$In\ Headache = 0.876 - 0.169RH + 0.067AM - 0.339CO_2 - 0.162HCHO \quad (4.24)$$

$$In\ Feeling\ Heavy\ Headed = 1.139 - 0.554T + 0.2AM - 0.208CO_2 \quad (4.25)$$

$$twoIn\ Fatigue\ or\ lethergy = 1.082 + 0.346T + 0.059AM - 0.476CO_2 - 0.934RSP + 0.008RH \quad (4.26)$$

$$In\ Drowsiness = 0.002 - 0.233T + 0.109AM + 0.744CO_2 + 0.085RH + 0.463HCHO \quad (4.27)$$

$$In\ Dizziness = 1.045 - 0.537T + 0.396AM + 0.354RH + 0.003CO_2 - 0.795HCHO \quad (4.28)$$

$$In\ Nausea\ or\ vomitting = 0.723 - 0.237T - 0.077RH - 0.041AM + 0.168CO_2 - 0.107HCHO \quad (4.29)$$

$$In\ Cough = 1.120 - 0.043T + 0.655RH - 0.101AM - 0.462CO_2 - 0.511RSP \quad (4.30)$$

$$In\ Hoarse\ or\ dry\ throat = 0.403AM + 0.293RH + 1.272CO_2 + 0.452HCHO - 0.221T - 0.446 \quad (4.31)$$

$$In\ Skin\ rash\ and\ Itchiness = 0.049 + 1.158T - 0.147RH + 0.461AM + 0.061HCHO + 0.458\ RSP \quad (4.32)$$

$$In\ Irritation\ of\ eye = 0.012T + 0.394RH + 0.129AM + 0.199RSP + 0.013CO_2 - 0.217 \quad (4.33)$$

NORTHEAST MONSOON

$$In\ Headache = 0.654 - 0.086T - 0.261RH + 0.706AM + 0.002CO_2 - 0.174HCHP - 0.202RSP \quad (4.34)$$

$$In\ Feeling\ Heavy\ Headed = 0.550 - 0.403T + 0.241RH + 0.584AM + 0.313\ CO_2 - 0.053HCHO + 0.061RSP \quad (4.35)$$

$$In\ Fatigue\ or\ lethergy = 0.381 - 0.587T + 0.402RH + 0.118AM + 0.704CO_2 - 0.013RSP \quad (4.36)$$

$$In\ Drowsiness = 0.505 + 0.193T - 0.083RH + 0.031AM + 0.115CO_2 - 0.128RSP \quad (4.37)$$

$$In\ Dizziness = 0.828 + 0.919T + 0.006RH - 0.034CO_2 - 0.373RSP \quad (4.38)$$

$$In\ Nausea\ or\ vomitting = 0.571 + 0.028T + 0.117RH + 0.014CO_2 - 0.090RSP \quad (4.39)$$

$$In\ Cough = 0.698 + 0.293T + 0.193RH - 0.101CO_2 - 0.008RSP \quad (4.40)$$

$$In\ Hoarse\ or\ dry\ throat = 0.639 + 0.262RH + 0.257CO_2 + 0.452HCHO - 0.257T - 0.570RSP \quad (4.41)$$

$$In\ Skin\ rashes\ and\ itchiness = 0.635RH + 0.770CO_2 + 0.287RSP - 0.013T - 0.135 \quad (4.42)$$

$$In\ Irritation\ of\ eye = 0.62 + 0.124T + 0.428RH - 0.441CO_2 - 0.157RSP \quad (4.43)$$

Table 4.26 shows a resume of the statistical model results performance for two models (SWM and NEM) for each dependent variable in S1. The first column of Table

4.26 presents the statistics tests most often used in generalized linear models and represent measures of dispersion (generalized and corrected), which permit testing the quality of models. Values from Table 4.26 confirm that model NEM, especially headache (22.904), fatigue or lethargy (27.048), and cough (26.643), has the lowest value, as shown by the statistical tests compared to SWM, which is headache (29.929), fatigue or lethargy (48.382) and cough (27.861) for AIC value. These statistical tests are obtained using all the deviations between the estimated and recorded (residuals) for each observation. Considering the Akaike Information Criterion, the objective is to minimise AIC. Model SWM such as feeling heavy-headed (-9.615), drowsiness (26.926), dizziness (23.084), nausea or vomiting (26.983), hoarse or dry throat (-16.331), skin rashness(34.382) and irritation of eye (28.631) has the lowest AIC of the two models, which means that the evidence for model NEM for feeling heavy-headed (-5.019), drowsiness (28.143), dizziness (32.389), nausea or vomiting (30.568), hoarse or dry throat (-15.205), skin rashness(41.362) and irritation of eye (34.952) is the best due to SWM has lowest AIC value than NEM. When comparing 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 two are suitable.

Table 4.26 Goodness of Fit (S3)

	SWM			**NEM**		
	Value	df	Value/df	Value	df	Value/df
Headache						
Deviance	0.643	10	0.064	.367	9	.041
Scaled Deviance	16.106	10		16.061	9	
Log Likelihood	-7.965			**-3.452**		
Akaike's Information Criterion (AIC)	29.929			**22.904**		
Finite Sample Corrected AIC (AICC)	43.929			**43.475**		
Feeling Heavy Headache						
Deviance	1.408	10	.141	0.798	9	0.089
Scaled Deviance	16.231	10		16.132	9	
Log Likelihood	-9.615			**-5.019**		
Akaike's Information Criterion (AIC)	33.230			**26.037**		
Finite Sample Corrected AIC (AICC)	47.230			**46.609**		
Fatigue Or Lethargy						
Deviance	.891	10	.089	0.499	9	0.055
Scaled Deviance	16.147	10		16.083	9	
Log Likelihood	34.382			**-5.524**		
Akaike's Information Criterion (AIC)	48.382			**27.048**		
Finite Sample Corrected AIC (AICC)	39.790			**47.620**		
Drowsiness						

Deviance	1.090	9	.121	1.330	10	.133
Scaled Deviance	16.180	9		16.219	10	
Log Likelihood	**-5.463**			-7.072		
Akaike's Information Criterion (AIC)	**26.926**			28.143		
Finite Sample Corrected AIC (AICC)	**47.497**			42.143		
Dizziness						
Deviance	.973	10	.097	1.727	10	.173
Scaled Deviance	16.160	10		16.283	10	
Log Likelihood	**-4.542**			-9.195		
Akaike's Information Criterion (AIC)	**23.084**			32.389		
Finite Sample Corrected AIC (AICC)	**37.084**			46.389		
Nausea and vomiting						
Deviance	1.387	10	.139	1.195	10	.119
Scaled Deviance	16.228	10		16.197	10	
Log Likelihood	**-2.983**			-8.284		
Akaike's Information Criterion (AIC)	**26.983**			30.568		
Finite Sample Corrected AIC (AICC)	**28.391**			44.568		
Cough						
Deviance	1.478	11	.134	1.212	10	.121
Scaled Deviance	16.243	11		16.199	10	
Log Likelihood	-7.931			**-6.321**		
Akaike's Information Criterion (AIC)	27.861			**26.643**		
Finite Sample Corrected AIC (AICC)	37.194			**30.643**		
Hoarse Or Dry Throat						
Deviance	1.846	11	.168	1.608	9	.179
Scaled Deviance	16.302	11		16.263	9	
Log Likelihood	**-16.331**			-15.205		
Akaike's Information Criterion (AIC)	**44.662**			46.409		
Finite Sample Corrected AIC (AICC)	**53.996**			66.981		
Skin Rash or Itchiness						
Deviance	1.153	10	.115	1.567	9	.174
Scaled Deviance	16.190	10		16.257	9	
Log Likelihood	**-10.191**			-12.681		
Akaike's Information Criterion (AIC)	**34.382**			41.362		
Finite Sample Corrected AIC (AICC)	**48.382**			61.933		
Irritation of Eye						
Deviance	1.155	10	.115	1.508	9	.168
Scaled Deviance	16.190	10		16.247	9	
Log Likelihood	**-7.315**			-9.476		
Akaike's Information Criterion (AIC)	**28.631**			34.952		
Finite Sample Corrected AIC (AICC)	**42.631**			55.524		

The Omnibus test was conducted in Table 4.27. An omnibus test is a comprehensive test employed to ascertain whether there are any overall effects or differences in a model or set of variables. It is used as an initial screening instrument to evaluate a general hypothesis regarding a collection of variables. The results of an omnibus test frequently indicate a significant effect, but they do not provide specific information regarding its location. The simplest way to understand the omnibus test is to determine whether there are any significant differences or relationships in a dataset. Due to the data collected having two different datasets, which are for SWM and NEM, the likelihood ratio chi-squared was calculated and used in the context of model fitting, such as in regression models or structural equation modelling, to compare nested models.

Model SWM such as dizziness (p=0.039), nausea or vomiting (p=0.010), hoarse or dry throat (p=0.021), skin rashness and itchiness (p=0.010) and irritation of the eye (p=0.015) has the lowest significance in Table 4.27, which shows the best significance when the likelihood ratio chi-square value is higher compared to NEM significant value for dizziness (p=0.043), nausea or vomiting (p=0.040), hoarse or dry throat (p=0.024), skin rashness and itchiness (p=0.058) and irritation of eye (p=0.026). The present symptoms of NEM include headache, feeling heavy-headed, fatigue or lethargy, drowsiness, and cough, which has the lowest significant value compared to the SWM model.

Table 4.27 Omnibus Test (S3)

	Likelihood Ratio Chi-Square	df	Sig.
Headache			
SWM	11.672	5	.040
NEM	**20.697**	**6**	**.002**
Feeling Heavy Headache			
SWM	4.034	5	.045
NEM	**13.227**	**6**	**.040**
Fatigue Or Lethargy			
SWM	4.130	5	.531
NEM	**13.463**	6	0.036
Drowsiness			
SWM	5.567	5	.051
NEM	**8.784**	6	.018
Dizziness			
SWM	**10.625**	5	.039
NEM	1.321	5	.043
Nausea and vomiting			
SWM	**7.281**	5	.010
NEM	6.696	5	.044
Cough			
SWM	3.849	4	.027
NEM	**7.067**	5	.016
Hoarse Or Dry Throat			
SWM	**15.722**	4	.021
NEM	7.975	6	.024

Skin Rash or Itchiness			
SWM	**10.208**	5	.010
NEM	5.228	6	.058
Irritation of Eye			
SWM	**7.954**	5	.015
NEM	3.633	6	.026

Table 4.22 showed equation of southwest monsoon and northeast monsoon at Mset Inflatable Composit Corporation Sdn. Bhd. (S3). Equation (4.44) – (4.53) was southwest monsoon and Equation (4.54)-(4.63) was northeast monsoon. Equation (4.44), Headache was increased by 0.504 unit when T variables go up by one unit, 0.422-unit, 0.134-unit, 0.815 unit and 0.113 unit in increasing one unit of RH, CO_2, TVOC and HCHO for headache in exponential term.

Equation (4.45), Feeling heavy headed increase 0.047-unit, 0.343 unit and 0.063, increase one unit of CO_2, TVOC and HCHO. Decrease 0.510 unit, and 0.836 unit of feeling heavy headed, when increase one unit of T and RH in exponential term.

Equation (4.46), Fatigue and lethargy increase 0.088 unit and 0.458 unit when increase one unit of T and RH. Increasing 0.96-unit, 0.114 unit and 0.327 unit of fatigue and lethargy, when increase one unit of CO_2, TVOC and HCHO in exponential term.

Equation (4.47), Drowsiness increase 0.192-unit, 0.196 unit and 0.329 unit when CO_2, CO and TVOC variables increase one unit, decrease 0.048 unit, 0.596 and 0.652 unit of drowsiness when increase one unit of T, RH, and HCHO in exponential term.

Equation (4.48), Dizziness increase 0.013 unit and 0.282 unit, when one unit of CO_2 and TVOC increase, decrease 0.662-unit, 1.254 unit and 0.576 unit of dizziness increase one unit of T, RH and HCHO in exponential term.

Equation (4.49), Nausea or vomiting increases by 0.316 units and 0.448 units when one unit of CO_2 and HCHO increase, decreases by 0.848-unit, 0.398 unit, and 0.487 unit of nausea or vomiting when one unit of T, RH and TVOC in an exponential term.

In equation (4.50), cough increases by 0.353 units, 0.293 units and 0.495 units when one unit of TVOC, HCHO and RSP increase decreases by 0.222 units of cough when one unit of T increases exponentially.

Equation (4.51), Hoarse and dry throat increase by 0.338 units and 0.401 units when one unit of T and TVOC increase, decrease by 0.939 unit and 0.084 units of hoarse and dry throat, when increasing one unit of HCHO and RSP in an exponential term.

Equation (4.52), Skin rashness and itchiness increased 0.680-unit, 0.172-unit, 0.171 unit and 0.649 unit when one unit of HCHO, RSP and AM increase, decrease 0.732 unit of skin rashness caused an increase of one unit of TVOC in an exponential term.

Equation (4.53), Irritation of the eye increased by 0.818 units and 0.329 units, when one unit of T and TVOC increased, a decrease of 0.135-unit, 0.419 unit and 0.023-unit irritation of the eye caused an increase of one unit of HCHO, RSP and AM in an exponential term.

Equation (4.54), Headache increases by 0.244-unit, 1.134 unit and 0.423unit when one unit of T, RH and CO_2 increases, decrease by 0.307 unit of headache when one unit of TVOC increases, increase by 0.037 unit of headache when one unit of RSP increase in exponential term.

Equation (4.55), Feeling heavy-headed increases by 0.664 units and 0.686 units when one unit of RH and HCHO decreases by 0.312-unit, 0.099 unit,0.529 unit and 0.277 units when one unit of T, CO_2, TVOC and RSP in an exponential term.

Equation (4.56), Fatigue or lethargy increase1.766-unit 0.048 unit,0.153-unit, 0.180 unit and 0.126 unit when one unit of RH, CO_2, TVOC, HCHO and RSP in the exponential term.

Equation of (4.57), Drowsiness increases by 1.32-unit, 0.269 unit and 0.629 units when one unit of RH, CO_2 and HCHO increases, decreases by 0.131 unit, and 0.380 unit of drowsiness when one one-unit TVOC and RSP in an exponential term.

Equation (4.58), Dizziness increases by 0.822 units when one unit of RH increases, decreases by 0.175 units, 0.118 units and 0.061 units of dizziness when one unit of TVOC, HCHO and RSP increases in the exponential term.

Equation (4.59), Nausea or vomiting increased by 0.943-unit, 0.183 unit and 0.266 units when increasing one unit of RH, TVOC and RSP, a decrease of 00.108 unit of nausea or vomiting caused an increase of one unit of HCHO in the exponential term.

Equation (4.60), Cough increases by 0.006 units, 0.805 units and 0.475 units when one unit of AM, HCHO and RSP decreases by 1.345 units and 0.252 units of cough when increasing one unit of T and RH exponentially.

Equation (4.61), Hoarse and dry throat increase 0.666-unit, 1.114 unit and 0.396 unit when one unit of T, RH and TVOC decreases 0.406 unit and 0.182 unit of hoarse or dry throat when one unit of HCHO and RSP increase in exponential terms.

Equation (4.62), Skin rash or itchiness increases by 1.548-unit, 1.930-unit, 0.439 units when one unit of T, RH, and AM increases, decreases 0.180 unit of skin rashness or itchiness when increasing one unit of TVOC, skin rashness and itchiness increase 0.017 unit, and 0.135 unit when one unit of HCHO and RSP increase in an exponential term.

Equation (4.63), Irritation of the eye increases by 1.429-unit, 1.517 unit,0.161 unit and 0.007 unit when one unit of T, RH, TVOC and AM increase, decreases 0.299 unit and 0.033-unit irritation of eyes, increase one unit of HCHO and RSP in exponential term.

Table 4.28 Equation of Mset Inflatable Composit Corporation Sdn. Bhd. (S3)

SOUTHWEST MONSOON	
$In\ Headache = 0.019 + 0.504T + 0.422RH + 0.134CO_2 + 0.815TVOC + 0.113HCHO$	(4.44)
$In\ Feeling\ Heavy\ Headed = 1.018 - 0.510T - 0.836RH + 0.047CO_2 + 0.343TVOC + 0.063HCHO$	(4.45)
$In\ Fatigue\ and\ lethergy = 0.312 + 0.088T + 0.458RH + 0.96CO_2 + 0.114TVOC + 0.327HCHO$	(4.46)
$In\ Drowsiness = 0.6 - 0.048T - 0.596RH + 0.192CO_2 + 0.192CO + 0.329TVOC - 0.652HCHO$	(4.47)
$In\ Dizziness = 1.278 - 0.662T - 1.254RH + 0.013CO_2 + 0.282TVOC - 0.576HCHO$	(4.48)
$In\ Nausea\ or\ Vomitting = 0.997 - 0.848T - 0.398RH + 0.316CO_2 - 0.487TVOC + 0.448HCHO$	(4.49)
$In\ Cough = 0.437 - 0.222T + 0.401TVOC - 0.939HCHO - 0.084RSP$	(4.40)
$In\ Hoarse\ or\ Dry\ Throat = 0.638 + 0.338T + 0.401TVOC - 0.939HCHO - 0.084RSP$	(4.51)
$In\ Skin\ Rashess\ or\ itchiness = 0.680T - 0.732TVOC + 0.172HCHO + 0.171RSP + 0.649AM - 0.191$	(4.52)
$In\ irritation\ of\ eye = 0.012 + 0.818T + 0.329TVOC - 0.135HCHO - 0.419RSP - 0.023AM$	(4.53)
NORTHEAST MONSOON	
$In\ Headache = 0.224T + 1.1348RH + 0.423CO_2 - 0.30TVOC + 0.483HCHO + 0.037RSP - 0.512$	(4.54)
$In\ Feeling\ Heavy\ Headed = 0.234 - 0.312T + 0.664RH - 0.099CO_2 - 0.529TVOC + 0.686HCHO - 0.277RSP$	(4.55)
$In\ Fatigue\ and\ lethergy = 0.683 + 1.766RH + 0.048CO_2 + 0.153TVO + 0.180HCHO + 0.216RSP$	(4.56)
$In\ Drowsiness = 0.532T + 1.32RH + 0.269CO_2 - 0.1131TVOC + 0.629HCHO - 0.380RSP - 0.987$	(4.57)
$In\ Dizziness = 0.903T + 0.822RH - 0.175TVOC - 0.118HCHO - 0.061RSP - 0.475$	(4.58)
$In\ Nausea\ or\ Vomitting = 1.671T + 1.943RH + 0.183TVOC - 0.108HCHO + -0.266RSP - 1.810$	(4.59)
$In\ Cough = 0.551 - 1.345RH + 0.006AM + 0.805HCHO + 0.475RSP$	(4.60)
$In\ Hoarse\ or\ Dry\ Throat = 0.666T + 1.114RH + 0.369TVOC - 0.406HCHO - 0.182RSP + 0.310AM$	(4.61)
$In\ Skin\ Rashess\ or\ itchiness = 1.548T + 1.930RH + 0.369TVOC - 0.406HCHO - 0.182RSP + 0.318AM$	(4.62)
$In\ irritation\ of\ eye = 1.429T + 1.517RH + 0.161TVOC - 0.229HCHO = 0.033RSP + 0.007AM - 1.281$	(4.63)

Table 4.29 shows a resume of the statistical model results performance for two models (SWM and NEM) for each dependent variable in S1. The first column of Table 4.29 presents the statistics test most often used in GLM and represents measures of dispersion that permit testing model quality. Values from Table 4.29 confirm that model NEM, especially headache (39.345), fatigue or lethargy (39.096), drowsiness (24.595),

dizziness (33.530), nausea or vomiting (15.518), cough (31.488), hoarse or dry throat (29.929) and irritation of the eye (49.851) has the lowest value, as shown by the statistical tests compared to SWM which is especially headache (40.301), fatigue or lethargy (40.452), drowsiness (36.139), dizziness (36.001), nausea or vomiting (35.642), cough (34.557), hoarse or dry throat (38.536) and irritation of the eye (51.117) for AIC value. These statistical tests are obtained using all the deviations between the estimated and recorded (residuals) for each observation. Considering the Akaike Information Criterion, the objective is to minimise AIC. Model SWM, such as feeling heavy-headed (47.921) and skin rashness (44.493), has the lowest AIC compared to NEM with feeling heavy-headed (49.995) and skin rashness (46.234). This showed that the best SWM model was for feeling heavy-headed and skin rash due to having the lowest AIC value compared to NEM. When comparing 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 two are suitable.

Table 4.29 Goodness of Fit (S4)

	SWM			**NEM**		
	Value	df	Value/df	Value	df	Value/df
Headache						
Deviance	.971	12	.081	1.039	12	.087
Scaled Deviance	18.160	12		18.172	12	
Log Likelihood	-13.151			**-12.673**		
Akaike's Information Criterion (AIC)	40.301			**39.345**		
Finite Sample Corrected AIC (AICC)	51.501			**50.545**		
Feeling Heavy Headache						
Deviance	1.523	12	.127	2.338	12	.195
Scaled Deviance	18.250	12		18.381	12	
Log Likelihood	**-16.960**			-17.998		
Akaike's Information Criterion (AIC)	**47.921**			49.995		
Finite Sample Corrected AIC (AICC)	**59.121**			61.195		
Fatigue Or Lethargy						
Deviance	1.766	12	.147	1.625	14	.116
Scaled Deviance	18.289	12		18.267	14	
Log Likelihood	-13.226			**-14.548**		
Akaike's Information Criterion (AIC)	40.452			**39.096**		
Finite Sample Corrected AIC (AICC)	51.652			**44.096**		
Drowsiness						
Deviance	1.524	12	.127	1.537	13	.118
Scaled Deviance	18.250	12		18.252	13	
Log Likelihood	-11.070			**-6.298**		
Akaike's Information Criterion (AIC)	36.139			**24.595**		

Finite Sample Corrected AIC (AICC)	47.339			**32.232**		
Dizziness						
Deviance	1.299	12	.108	1.590	13	.122
Scaled Deviance	18.214	12		18.261	13	
Log Likelihood	-11.000			**-10.765**		
Akaike's Information Criterion (AIC)	36.001			**33.530**		
Finite Sample Corrected AIC (AICC)	47.201			**41.167**		
Nausea and vomiting						
Deviance	1.483	12	.124	.372	13	.029
Scaled Deviance	18.244	12		18.062	13	
Log Likelihood	-10.821			**-1.759**		
Akaike's Information Criterion (AIC)	35.642			**15.518**		
Finite Sample Corrected AIC (AICC)	46.842			**23.155**		
Cough						
Deviance	1.755	12	.146	1.655	13	.127
Scaled Deviance	18.288	12		18.272	13	
Log Likelihood	-10.278			**-9.744**		
Akaike's Information Criterion (AIC)	34.557			**31.488**		
Finite Sample Corrected AIC (AICC)	45.757			**39.124**		
Hoarse Or Dry Throat						
Deviance	1.266	12	.105	1.070	12	.089
Scaled Deviance	18.208	12		18.176	12	
Log Likelihood	-12.268			**-7.964**		
Akaike's Information Criterion (AIC)	38.536			**29.929**		
Finite Sample Corrected AIC (AICC)	49.736			**41.129**		
Skin Rash or Itchiness						
Deviance	1.288	13	.099	1.388	12	.116
Scaled Deviance	18.212	13		18.228	12	
Log Likelihood	**-16.247**			-16.117		
Akaike's Information Criterion (AIC)	**44.493**			46.234		
Finite Sample Corrected AIC (AICC)	**52.130**			57.434		
Irritation of Eye						
Deviance	1.735	12	.145	2.394	12	.199
Scaled Deviance	18.284	12		18.390	12	
Log Likelihood	-18.559			**-17.925**		
Akaike's Information Criterion (AIC)	51.117			**49.851**		
Finite Sample Corrected AIC (AICC)	62.317			**61.051**		

In Table 4.30, the Omnibus test was run. An omnibus test is a comprehensive test used to determine whether there are any overarching effects or differences in a model or set of variables. It is an initial screening instrument to assess a general hypothesis concerning variables. The results of an omnibus test often suggest a substantial effect; however, they do not offer precise information regarding its location. The most straightforward method of comprehending the omnibus test is to ascertain whether there are any significant relationships or differences in a dataset. The likelihood ratio chi-squared was calculated and employed in the context of model fitting, such as in regression models or structural equation modelling, to compare nested models, as the data collected consisted of two distinct datasets: the southwest monsoon (SWM) and the northeast monsoon (NEM).

Model SWM such as feeling heavy-headed (p=0.07), skin rashness and itchiness (p=0.019) and irritation of the eye (p=0.043) has the lowest significance in Table 4.30, which shows the best significance when the likelihood ratio chi-square value is higher compared to NEM significant value for feeling heavy headed (2.007) skin rashness and itchiness (13.699) and irritation of the eye (5.638). The present symptoms of NEM include headache, fatigue or lethargy, drowsiness, nausea or vomiting, cough, and hoarse and dry throat, which has the lowest significant value compared to the SWM model.

Table 4.30 Omnibus Test[a] (S4)

	Likelihood Ratio Chi-Square	df	Sig.
Headache			
SWM	6.378	5	.019
NEM	**12.676**	**5**	**.000**
Feeling Heavy Headache			
SWM	**2.007**	**5**	**.007**
NEM	2.013	5	.847
Fatigue Or Lethargy			
SWM	7.791	5	.068
NEM	**12.522**	**3**	**.047**
Drowsiness			
SWM	4.224	5	.018
NEM	**11.610**	**4**	**.007**
Dizziness			
SWM	3.201	5	.049
NEM	**4.585**	**4**	**.033**
Nausea and vomiting			
SWM	4.722	5	.045
NEM	**11.795**	**4**	**.019**
Cough			
SWM	3.702	5	.033
NEM	**4.772**	4	.012
Hoarse Or Dry Throat			
SWM	18.284	5	.030
NEM	**27.082**	**5**	**.015**
Skin Rash or Itchiness			
SWM	**13.699**	**5**	**.019**
NEM	6.456	4	.048
Irritation of Eye			
SWM	**5.638**	**5**	**.043**
NEM	.448	5	.094

Table 4.31 shows the southwest and northeast monsoon equation at Raia Hotel & Convention Centre Terengganu (S4). Equation (4.64) Headache was increased by 0.187 unit when T variables go up by one unit, 0.428 unit in decreasing one unit of RH, 0.235 unit for the decreasing in one unit of AM, 0.449 unit when CO_2 decreased by one unit, and 0.303 unit decreased in one unit of RSP in exponential term.

Equation (4.65), Feeling heavy headed was increased by 0.006 when T variables go up by one unit, 0.381 unit of RH in decreasing one unit of feeling heavy headed, increased 0.070 unit of feeling heavy headed caused AM to go up one unit, decreasing 0.421 unit and 0.397 unit of feeling heavy headed, increased one unit of CO_2 and RSP in exponential term.

Equation (4.66), Fatigue or lethargy increased by 0.263 units when RSP variables went up one unit, 0.102 unit,0.461-unit,0.475unit and 0.825 unit of fatigue and lethargy increased when one unit of T, RH, AM, and CO_2 in an exponential term.

Equation (4.67), Drowsiness increased by 0.141 unit when T variables went up one unit, 0.014 unit and 0.236 unit of drowsiness increased when one unit of AM and CO_2 increased, decreasing 0.596 unit and 0.350 unit of drowsiness increased when one unit of RH and RSP decreased in exponential term.

Equation (4.68), Dizziness increases by 0.015 units and 0.162 units when one unit of RH and AM increases one unit, decreases by 0.510unit, 0.122unit and 0.286 unit of dizziness when increasing one unit of T, CO_2 and RSP in an exponential term.

Equation (4.69), Nausea or vomiting increases by 0.111 units when one unit of T increases, decreases by 0.308 units of nausea or vomiting when one unit of T, decreases by 0.483 units, 0.410 units and 0044 units of nausea or vomiting when increasing one unit of AM, CO2, and RSP in exponential term.

Equation (4.70): Cough increased by 0.253 units and 0.254 units when one unit of T and CO_2 increased, decrease by 0.189 unit and 0.361 unit of cough when increase of one unit of RH and RSP, increase of 0.058 unit of cough when one unit of AM increase in the exponential term.

Equation (4.71), Hoarse or dry throat increased by 1.189 units and 0.574 units when RH and RSP increased one unit, decreased by 0.229-unit, 0.40 unit, and 0.482 unit of hoarse or dry throat when one unit of T, AM, and CO_2 increase in exponential terms in exponential term.

Equation (4.72), skin rash and itchiness increase by 0.037 units and 0.018 units when one unit of RH and AM increase, decrease by 0.547-unit, 0.015 unit and 0.388 unit of skin rash and itchiness when increasing one unit of T, CO_2 and RSP in exponential term.

Equation (4.73), eye irritation increases by 0.725 units and 0.199 units when one unit of RH and AM decreases by 0.433 units, 0.361 units and 0.872 units of eye irritation when one unit of T, CO_2 and RSP is in exponential terms.

Table 4.31 shows the equation of the northeast monsoon at Raia Hotel & Convention Centre Terengganu (S4). Equation (4.74), Headache increases by 0.377 units, 0.266 units, 0.451 units and 0.076 units when T, RH, CO_2 and RSP increase one unit, decreases by 0.073 units of headache when increasing one unit of AM exponentially.

Equation (4.75), Feeling heavy-headed increases by 0.378-unit, 0.394 unit and 0.272 units, when increasing one unit of T, CO_2 and RSP, decreases by 0.147 unit and 0.378 unit of feeling heavy headed when one unit of AM and RH increase in exponential term.

Equation (4.76), Fatigue and lethargy increase by 0.259 units when one unit of T increases, 0.730 units of fatigue and lethargy increase when one unit of AM increases and increase by 0.308 unit of fatigue and lethargy when one unit of CO_2 in an exponential term.

Equation (4.77), Drowsiness increases by 0.370 units and 0.086 units when one unit of T. RSP decreases drowsiness by 0.070 units and 0.074 units when increasing one unit of AM and RH in an exponential term.

Equation (4.78), Dizziness increases by 0.067 units when one unit of T decreases by 0.610 units, 0.253 units and 0.673 units when increasing one unit of AM, RSP and CO_2 exponentially.

Equation (4.79), Nausea or vomiting increase by 0.892 units and 0.146 units when one unit of T and CO_2 increase, decreases by 0.165 units and 0.303 units of nausea or vomiting when one unit of AM and RSP in exponential term in an exponential term.

Equation (4.80), Cough increases by 1.004 units and 0.911 units when one unit of RH and CO_2 decreases by 0.062 units and 0.026 unit of cough increases exponentially by one unit of T and AM.

Equation (4.81), Hoarse and dry throat increase by 0.953 units when one unit of T increases, decrease by 0.367-unit, 0.285-unit, 0.012 unit and 0.284 unit of the hoarse and dry throat when one unit of AM, CO_2, RH and RSP in exponential term.

Equation (4.82), Skin rashness and itchiness increase by 1.084 units and 0.225 units when increasing one unit of T and AM and decrease by 0.226 units and 1.458 units when increasing one unit of CO_2 and RH in an exponential term.

Equation (4.83), Irritation of the eyes increases by 0.169 unit, 0.261 unit and 0.032 unit when one unit of T, AM and CO_2 decreases by 0.023 unit when increasing one unit of RH in an exponential term.

Table 4.31 Equation of Raia Hotel and Convention Centre (S4)

SOUTHWEST MONSOON	
$In\ Headache = 1.355 + 0.187T - 0.428RH - 0.235AM - 0.449CO_2 - 0.303RSP$	(4.64)
$In\ Feeling\ Heavy\ Headed = 1.245 - 0.006T - 0.381RH + 0.070AM - 0.421CO_2 - 0.397RSP$	(4.65)
$In\ Fatigue\ and\ lethergy = 1.242 + 0.102T - 0.461RH - 0.475AM - 0.825CO_2 + 0.263RSP$	(4.66)
$In\ Drowsiness = 0.847 + 0.141T - 0.596RH + 0.014AM + 0.236CO_2 - 0.350RSP$	(4.67)
$In\ Dizziness = 0.869 - 0.510T + 0.015RH + 0.162AM - 0.122CO_2 - 0.286RSP$	(4.68)
$In\ Nausea\ or\ Vomitting = 0.890 - 0.308T + 0.111RH - 0.483AM - 0.410CO_2 - 0.044RSP$	(4.69)
$In\ Cough = 0.422 + 0.253T - 0.189RH + 0.058AM + 0.058AM + 0.254CO_2 - 0.361RSP$	(4.70)
$In\ Hoarse\ or\ Dry\ Throat = 1.189RH - 0.229T - 0.408AM - 0.482CO_2 + 0.574RSP - 0.121$	(4.71)
$In\ Skin\ Rashess\ or\ itchiness = 1.179 - 0.547T + 0.037RH + 0.018AM - 0.015CO_2 - 0.388RSP$	(4.72)
$In\ irritation\ of\ eye = 1.785 - 0.433T + 0.725RH + 0.199AM - 0.361CO_2 - 0.872RSP$	(4.73)
NORTHEAST MONSOON	
$In\ Headache = 0.305 + 0.377T - 0.073AM + 0.266RH + 0.451CO_2 + 0.076RSP$	(4.74)
$In\ Feeling\ Heavy\ Headed = 0.589 + 0.378T - 0.147AM - 0.378RH + 0.394CO_2 + 0.272RSP$	(4.75)
$In\ Fatigue\ and\ lethergy = 0.005 + 0.259T + 0.703AM + 0.308CO_2$	(4.76)
$In\ Drowsiness = 0.266 + 0.370T - 0.070AM - 0.074RH + 0.086RSP$	(4.77)
$In\ Dizziness = 1.002 + 0.067T - 0.610AM - 0.253RSP - 0.673CO_2$	(4.78)
$In\ Nausea\ or\ Vomitting = 0.459 + 0.953T - 0.367AM - 0.285CO_2 - 0.012RH - 0.284RSP$	(4.79)
$In\ Cough = 0911RH - 0.062T - 0.026AM + 1.004CO_2 - 0.417$	(4.80)
$In\ Hoarse\ or\ Dry\ Throat = 0.666T + 1.114RH + 0.369TVOC - 0.406HCHO - 0.182RSP + 0.310AM$	(4.81)
$In\ Skin\ Rashess\ or\ itchiness = 0.861 + 1.084T + 0.255AM - 0.226CO_2 - 1.458RH$	(4.82)
$In\ irritation\ of\ eye = 0.591 + 0.169T + 0.261AM + 0.032 + 0.032CO_2 - 0.023RH = 0.121RSP$	(4.83)

The forecasted SBS symptoms (dependent variables) concentrations for the model derived at all sites were plotted in Table 4.32 against observed values to determine a good fit of the models for both SWM and NEM at each study area. The regression lines also show a 95% confidence interval. Table 4.32 presents the R^2 values, a statistical measure used to evaluate the accuracy of the forecasted SBSS in relation to the observed SBS symptoms data. The R^2 values provide insight into how well the forecasted model aligns with actual conditions across various study areas, with higher values indicating a better fit between the forecasted and observed data. Most of the points fall within a 95% confidence interval range. The R^2 for headache validation was 0.8225 during SWM and 0.9597 for NEM at S1, same with others study areas which consist of S2, S3, and S4 for northeast monsoon (NEM) has the highest value of R^2 than

SWM model for headache symptoms. Sekolah Kebangsaan Tanjung Gelam (S1) has the highest value of R^2 during NEM with 0.9597 and the lowest value of headache model located at Raia Hotel & Convention Centre Terengganu (S4) during the SWM (R^2=0.5485).

Feeling heavy is one of the indicators contained in SBSS; the study showed that R^2 for all study areas or sites was between 0.5801 (S1)—0.7397(S4) for SWM and 0.5815 (S1)—0.7930(S3) for NEM. Each site's lowest values for both monsoons for feeling heavy-headed symptoms in Table 4.32 were S1 (R^2=0.5801, SWM), S2 (R^2=0.6407, NEM), S3 (R^2=0.7129, SWM), and S4 (R^2=0.6820, NEM).

Fatigue and lethargy were the subsequent symptoms experienced by the workers in all study areas during SWM and NEW. In comparison to NEM (R^2=0.6035), SWM (R^2 =0.7937) exhibited a higher R^2 value for fatigue and discomfort (S1). R^2=0.5918 is the value of NEM for S2, which is greater than the value of SWM (R^2=0.5252). S3 demonstrated that the NEM (R^2=0.8119) model had a more excellent value than the SWM (R^2=0.7263) model. Lastly, the S4 model was more valuable during the NEM (R^2=8675) period than the SWM (R^2=0.6823) period.

The questionnaire included a query regarding drowsiness, which was a significant SBS symptoms. The value of S1 is lesser in NEM (R^2=4014) than in SWM (R^2=0.7797). Table 4.32 demonstrated that S2 exhibits a higher value during NEM (R^2=0.6590) than SWM (R^2=5644). S3 is significantly higher during SWM (R^2=0.8752) than during NEM (R^2=0.5766). According to S4, the R^2 value for NEM was 0.7673, higher than that of SWM (0.5192).

The R^2 value during NEM was superior to that of SWM, as evidenced by the dizziness in S1. Specifically, for SWM, the R^2 was 0.9949, while for NEM, it was 0.5834. The R^2 value of S2 is 0.6159 (SWM), which is higher than the R^2 value of 0.5380 (NEM). S3 exhibits a lower value during NEM (R^2=0.5766) than SWM (R^2=6159). Compared to SWM (R^2=0.7400), S4 exhibits a higher R^2 value during NEM (R^2=0.8792).

The R^2 value for nausea and vomiting at S1 is higher during SWM at 0.9070 than in NEM at 0.7704. S2 exhibits a higher R^2 during NEM (0.800) than SWM (0.6478). Then, S3 has a lower R^2 value during NEM (0.7310) than SWM (0.8476). S4 was higher during NEM (0.8447) than SWM (0.6293).

The next subject is cough, and S1 demonstrated that SWM (R^2= 0.8180) has a higher R^2 value than NEM (R^2= 0.5465). S2 exhibited a poorer R^2 value (0.6144) during NEM than SWM (0.6490). The R2 value was significantly higher during the northeast monsoon (R^2=8970) than during the southeast monsoon (R^2=0.5957), as demonstrated by S3. S4 exhibits a high value of 0.8071 during NEM, in contrast to SWM R^2 of 0.5279.

The R^2 value for hoarse and dry throat is higher during SWM (0.8182) than during NEM (0.7751). S2 has the most significant value during NEM with R^2=0.5850 and SWM with R^2=0.5543. The S3 value was significantly higher during SWM (0.8476) than the R^2 value of the NEM (0.800). Finally, S4 exhibits a lower R^2 value during SWM (0.6664) than NEM, which has R^2=0.53539.

The R^2 value for skin rashness or itchiness is most significant during NEM, with an R^2 of 0.9288, compared to SWM, which has an R^2 =0.9240 at S1. Similarly, the R^2 value for S2 is highest during NEM compared to SWM. The R^2 value of S3 during SWM is 0.8760, significantly higher than that of NEM, which is 0.7041. Similarly, S4 has the most outstanding R^2 value during SWM, which is higher than that of NEM.

The R^2 value of SWM (0.9355) is the highest compared to NEM (0.9016) for eye irritation. Conversely, S2 has a high R^2 value with NEM (R^2=0.5457) and SWM (R^2=0.5383). S3 demonstrated that the R^2 value was maximum during SWM (R^2=0.8271) compared to NEM (R^2=0.6724). The final site, S4, demonstrated that the R^2 value was equally high for both monsoonal seasons (R^2=0.5284).

Table 4.32 Comparative R^2 Values of Forecasted SBS symptoms Versus Observed SBS symptoms Across All Study Areas

Symptoms	Site	SWM	NEM
Headache	S1	0.8225	0.9597
	S2	0.6284	0.6969
	S3	0.6755	0.7129
	S4	0.5485	0.6404
Feeling heavy headache	S1	0.5801	0.5815
	S2	0.7177	0.6407
	S3	0.7129	0.7930
	S4	0.7397	0.6820
Fatigue or lethargy	S1	0.7937	0.6035
	S2	0.5252	0.5918
	S3	0.7263	0.8119
	S4	0.6829	0.8675
Drowsiness	S1	0.7797	0.4014
	S2	0.5644	0.6590
	S3	0.8752	0.5766
	S4	0.5192	0.7673
Dizziness	S1	0.5834	0.9949
	S2	0.6159	0.5380
	S3	0.8257	0.5766
	S4	0.7400	0.8792
Nausea and vomiting	S1	0.7704	0.9070
	S2	0.6478	0.800
	S3	0.8476	0.7310
	S4	0.6293	0.8447
Cough	S1	0.8180	0.5465
	S2	0.6490	0.6144
	S3	0.5957	0.8970
	S4	0.5209	0.8071
Hoarse and dry throat	S1	0.8182	0.7751
	S2	0.5543	0.6420
	S3	0.8476	0.800
	S4	0.6664	0.8389
Skin rash or itchiness	S1	0.9240	0.9288
	S2	0.5472	0.5850
	S3	0.8760	0.7041
	S4	0.6277	0.5108
Irritation of eye	S1	0.9355	0.9016
	S2	0.5383	0.5457
	S3	0.8271	0.6724
	S4	0.5284	0.5284

4.1.6 Model Validation

4.2 Discussion

The discussion of each objective in the completion of this chapter is illustrated in this section. Section 4.2.1 discussed sick building syndrome (SBS) symptoms and compliance with indoor air pollutants (IAP) with the standard in each study area, representing the sub-dominant economy in Terengganu. The discussion of computational fluid dynamics simulation for all study areas is illustrated in Section 4.2.2, while the discussion of the principal component analysis (PCA) is presented in Section 4.2.3. Finally, a gamma model was employed to construct and validate a generalized linear model (GLM) for each study area with distinct monsoonal seasons.

4.2.1 A discussion regarding the symptoms of Sick Building Syndrome (SBS) symptoms and the corresponding compliance for indoor air quality (IAQ)

Pat 3-month symptoms

Past 3-month symptoms consist of draught, room temperature too high, varying room temperature, room temperature too low, stuffy bad air, dry air, unpleasant odour, passive smoking, dust, and dirt. Most workers agreed that they faced drought for the past three months with the answer "Yes, sometimes". The sensitivity to draught is increased in vented areas due to higher air velocity and turbulence, which are influenced by several factors (Vardoulakis *et al.*, 2020). This increased sensitivity is particularly noticeable around the head region. In addition, the impression of draughts is affected by the air temperature, as lower temperatures increase the chances of experiencing discomfort (Markov *et al.*, 2020). Efficient control of ventilation systems and external factors is essential for maintaining a balance between interior air quality and thermal comfort while reducing the discomfort caused by draughts (Maung *et al.*, 2022). The perception of air movement and draughts in indoor situations is affected by various factors, including air velocity, temperature, turbulence, and individual thermal sensation (Mutlu, 2020). Periodic changes in air movement can improve thermal comfort without creating a draught, whereas elevated temperatures typically increase the tolerance for air circulation (Bhattacharya *et al.*, 2020). Human activity and the rate at which air changes also significantly impact the formation of interior airflow patterns and air quality (Gao *et al.*, 2020). Gaining knowledge of these factors can assist in maximising interior environments for enhanced comfort and air quality (Wang & Norback, 2021).

Room temperature too high is a considerable proportion of individuals experiencing room temperatures as too high, a perception that is frequently linked to elevated absolute air humidity and fluctuating room temperatures (Zuo *et al.*, 2020). Higher indoor temperatures, particularly over 30°C, in conjunction with elevated humidity levels, result in heightened physiological strain and discomfort, hence reducing the acceptability of indoor air quality (Wang & Norbäck, 2021). 45.0% of the participants perceived too high room temperature, which can indicate a poor thermal environment (Wang & Norback, 2021). A previous study found that 45.5% of the residents in S1 agreed that the temperature in their workplace, namely the teacher's room, was too hot. Among the teachers, 45.5% answered "Yes, sometimes" during the study for both monsoonal variations, whereas 88.9% answered the same during SWM and 66.7% during NEM at S3.

Varying room temperature in conjunction with elevated humidity (70%) has a substantial impact on physiological strain (such as increased heart rate and respiration rate) and discomfort, resulting in a decline in perceived air quality and an increase in symptoms of SBS symptoms (Capua *et al.*, 2023; Tsoulou *et al.*, 2021). Peak cognitive and occupational performance is attained within the temperature range of 22°C to 24°C. Varying room temperatures may reduce performance and heighten health hazards, such as dry eyes and respiratory symptoms (Mansouri *et al.*, 2022; Chang *et al.,* 2015). Occupants in all study areas mostly agreed that they face varying room temperatures, and only a few workers disagreed for both monsoonal areas at all parameters, as shown in Table 4.2

The study revealed that the room temperature in the study areas, namely TMG Mart (S2) and Raia Hotel Convention Centre Terengganu (S4), was often temperature too low at a particular time. The occupants of these workplaces agreed that the temperature was sometimes too low, with 66.7% (SWM) and 60.6% (NEM) of S2 occupants and 33.3% (SWM) and 66.7% (NEM) of S4 occupants answering "Yes, sometimes". Additionally, 66.7% of S4 occupants answered "Yes, often" when asked if the temperature was too low, as shown in Table 4.2. Low room temperatures can substantially impact indoor air quality by influencing thermal comfort, health, and overall environmental quality (Wilby *et al.,* 2021; Wolkoff, 2018). The ideal indoor temperatures for comfort and performance often range from 22°C to 24°C (Nagy *et al.*, 2022). Low temperatures, frequently combined with reduced humidity, can increase health risks and discomfort (Liu *et al.*, 2022). Adequate air movement and adequate building insulation are crucial in reducing these adverse impacts and ensuring a stable and healthful interior atmosphere (Wilby *et al.*, 2021).

Prolonged exposure to insufficient indoor air quality, characterised by stuffy bad air, can result in many health issues, including illness, increased absenteeism, reduced focus, fatigue, drowsiness, and undesirable symptoms such as respiratory problems or headaches (Mansor *et al.*, 2024; Vornanen-Winqvist *et al.*, 2020). It can also contribute to impaired performance in daily activities (Lolliet *et al.*, 2022; Wen *et al.*, 2019). The findings of this study revealed that a significant majority of workers at S1 experienced poor air quality, with 90.9% reporting stuffy air during the southwest monsoon (SWM) and 81.8% reporting the same during the northeast monsoon (NEM). In addition to the 63.6% occurrence during SWM and 51.5% during NEM for S2, there was a 75% occurrence during SWM and 62.5% during NEM for S3. Furthermore, in the last study area, S4, 61.1% agreed that individuals experienced stuffy and poor air quality, with a frequency of "Yes, sometimes" occurring approximately 2-3 times per week.

Dry air is one of the past 3-month symptoms asked in the questionnaire. Moisture recovery systems in residential ventilation significantly decrease the number of hours of dry air compared to heat recovery systems, improving indoor air humidity and health (Kremer *et al.*, 2021). The presence of dry air within a structure can be attributed to various reasons, all of which can contribute to a decrease in interior humidity. These factors include the heating system (Awada *et al*., 2022; Demanega *et al.*, 2021), air conditioning (Kumar *et al.*, 2023; Nezis *et al.*, 2019), ventilation (Tran *et al.*, 2020), outdoor climate (Asumadu-Sakyi *et al.*, 2019), building material (Sarkar, 2019), dehumidifier (Awada *et al*., 2021; Park *et al.*, 2019), and seasonal variations (Mansouri *et al.*, 2022; Kuang, 2020). One way to combat dry air should consider employing a humidifier to introduce moisture, enhance airflow, or ensure the appropriate functioning of heating and cooling systems (Byber *et al.*, 2021; Chang *et al*., 2015). Perceived "dry air" in indoor environments is caused by low indoor air humidity, indoor air pollutants, dry eyes and throat, and nasal diseases, with potential links to dry eyes, throat, and respiratory issues (Zainordin *et al.*, 2022; Wolkoff, 2018).

The questionnaire enquired about an unpleasant odour; most workers reported not experiencing it as a symptom over the last three months. Specifically, 45.5% of NEM and SWM workers at S1 disagreed, while 6.1% of SWM workers and 12.1% of NEM workers disagreed at S2. Additionally, 38.9% of workers reported experiencing the stench during both monsoon seasons at S4, while no workers answered "No, never" at S3. Enhancing the intensity of ventilation in indoor environments has been found to increase the perceived air quality and decrease the intensity of odours. This improvement in air quality and reduced odours contribute to the comfort and health of the individuals occupying the building (Chattopadyay & Shaw, 2021; Kraus & Senitkova, 2019). Displacement of ventilation systems in buildings has the potential to enhance air quality. However, it is essential to note that the downward airflow along walls may increase the concentration of contaminants in the occupied area, as Choi *et al.* (2020) highlighted. This statement explains why workers at that site never experience unpleasant odours. The building has big windows and doors that allow for proper ventilation (Chuang *et al.,* 2023). A blower is installed within the structure to enhance the ventilation system further.

According to Kuga *et al.* (2020), smoking in enclosed areas may worsen indoor air quality and pose health concerns to occupants. Research conducted by Khoa *et al.* (2023) has proven that the aerosols inhaled by secondary smokers or passive smokers are a secondary source of emissions in indoor environments. Passive smokers can be exposed to these aerosols through both respiratory and cutaneous pathways, which can lead to symptoms such as drowsiness and a dry, hoarse throat. The study found that passive smoking is positively correlated with hoarse dry throat symptoms during NEM ($r=0.591$, $p<0.01$) and SWM ($r=0.581$, $p<0.05$). Additionally, passive smoking is significantly associated with drowsiness during NEM at S2 ($r=0.452$, $P<0.01$) and during SWM ($r=0.552$, $p<0.01$), which is shown in additional analysis in Appendix B.

Over the previous three months, the most recent symptoms experienced were related to dust and dirt. These factors can be attributed to open windows and doors, unclean air filters, and routine daily activities. Irrespective of the underlying reason, the presence of airborne dust indoors can lead to significant health problems. Individuals with allergies and asthma are more likely to be conscious that dust significantly negatively influences respiratory health (Nazzal *et al.*, 2023; Ezhumalai *et al.*, 2021). Indoor particulate matter (PM) or respirable suspended particulate (RSP) can have severe health effects and is a potential health hazard due to people spending most of their time indoors (Zhang *et al.*, 2021; Maskova *et al*., 2020). Indoor air pollution, particularly RSP, is associated with reduced lung function, oxygen saturation, childhood asthma, and chronic obstructive pulmonary disease (COPD) symptoms towards occupants (Maung *et al.*, 2022). Indoor concentrations of RSP are higher than outdoors, increasing during working hours, and are associated with health effects like eye irritation, dry throat, runny nose, sneezing, cough, tiredness, irritability, headache, dizziness, and skin irritation (Nezis *et al.*, 2019). According to the results, most workers acknowledged being exposed to dust and filth (Table 4.2). The percentage of occurrence during the Southwest Monsoon (SWM) and Northeast Monsoon (NEM) at S1 is 81.8%. During both monsoonal seasons at S2, the percentage is 75.8%. In S3, the percentages are 12.5% during SWM and 6.25% during NEM; in S4, the percentages are 16.7% during SWM and 27.8% during NEM. The answer to "Do these events occur?" is "Yes, sometimes." Only S4 workers have a significantly high percentage, 77.8%, who disagree with the statement that they encountered dust and dirt during SWM. Additionally, 55.6% of S4 workers responded with "No, never" when asked about this issue.

Present symptoms

The initial present symptom was headache. The majority of the workers in the study area, who represent sub-dominant economies or sub-sectors of education, wholesale and trade, manufacturing, and hospitality, reported experiencing headaches on a "Yes, sometimes" or "Yes, often" basis more than 50% workers (refer to Table 4.3). Elevated concentrations of respirable suspended particulate (RSP) or particulate matter ($PM_{2.5}$ and PM_{10}) in workplace settings are linked to a range of health issues, such as headaches (Nezis *et al.*, 2019). Indoor levels of RSP frequently surpass the guidelines set by the World Health Organization (WHO), particularly in buildings that rely on classic ventilation, such as fans and blowers (Felgueiras *et al.*, 2022; Kapalo *et al.*, 2020). This remark aligns with the findings of the survey, which indicate that the most significant percentages of workers who answered "Yes, sometimes" were from the teachers' room at Selolah Kebangsaan Tanjung Gelam (S1) (72.7%, SWM; 72.7%, NEM) and Mset Inflatable Composit Corporation Sdn. Bhd (S3) (68.8%, SWM; 87.5%, NEM), both of which have classic ventilation compared to S2 and S4 which used air-conditioning. Excessive levels of indoor pollutants in workplaces are linked to heightened health symptoms, such as headaches, exhaustion, and dermatological problems (Sakellaris *et al.*, 2020).

The second symptom that has been assessed is experiencing a sensation of heaviness in the head or feeling heavy-headed. Indoor air pollution significantly contributes to chronic diseases and poses a substantial health risk for residents (Mentese *et al.*, 2020). An initial symptom experienced was a sensation of heaviness in the head, which can be attributed to elevated levels of indoor air pollutants within buildings. These higher pollutant levels are linked to sick building syndrome symptoms, whereas lower levels are connected with improved respiratory health within buildings (Campagna & Desai, 2019). Prolonged exposure to poor indoor air quality can result in several health issues, including illness, absenteeism, reduced focus, fatigue, drowsiness, respiratory problems, mental sluggishness, and lower activity performance (Mansor *et al.*, 2024; Dang *et al.,* 2022). The findings of this study were supported by most workers who reported feeling heavy-headed. This was indicated by their "Yes, sometimes" responses across all study areas, as shown in Table 4.3.

The workers experienced indications of fatigue and lethargy. Further investigation is required to tackle work-induced exhaustion in high-risk worker groups, considering various risk categories and poor indoor air quality (Cunningham *et al.*, 2022). Mainka *et al.* (2019) state that increasing ventilation during working hours can reduce CO_2 concentration by 55-64% without compromising thermal comfort or causing weariness or lethargy among occupants. This finding is significant because most individuals in the study region reported experiencing exhaustion or lethargy. Specifically, 63.6% of teachers in the teachers' room reported feeling this way during the monsoon season in S1, while 48.5% reported the same in S2 (Table 4.3). At S4, the percentages were 66.7% for SWM and 50% for NEM. These respondents indicated that they sometimes felt fatigue or lethargy. Fatigue can arise from a mix of reasons, including medical diseases, illnesses, bad lifestyle choices, employment issues, poor indoor air quality, bereavement, and stress (Goudarzi *et al.*, 2024; Xiao *et al.*, 2021; Settimo *et al.*, 2020; Sadick *et al.*, 2020). According to Tran *et al.* (2020), it is necessary to have appropriate work balances and comfortable working environments in order to prevent these symptoms.

Dizziness and drowsiness are frequently confused by many individuals due to their similar tone, leading them to believe that they are synonymous mistakenly. In short, dizziness refers to the sensations of syncope, unbalance, and a swirling feeling, while sleepiness is a condition that includes excessive and uncontrollable sleep (Salju *et al.*, 2023; Aziz *et al.,* 2023). Elevated levels of carbon dioxide (CO_2) and air pollutants, such as total volatile organic compounds (TVOC) and formaldehyde (HCHO), in the workplace are known to be contributing factors to drowsiness (Choi *et al.*, 2020; Awada *et al.*, 2021). Office plants have the potential to decrease CO_2 levels and potentially mitigate CO_2-related health issues, such as drowsiness and increased systolic blood pressure (Chuang *et al.*, 2023; Vardoulakis *et al.*, 2020). Additionally, regulating air conditioning and lighting settings can enhance the productivity of office workers by 8.3% while maintaining comfort and reducing tiredness and headaches (Byber *et al.*, 2021; Kogo *et al.*, 2019). A prior study examines the sources of indoor air pollution and suggests novel architectural approaches to mitigate indoor air pollution. This study aims to tackle the increasing problem of sick building syndrome in residential and occupational settings, particularly symptoms such as headaches, fatigue, dizziness, drowsiness, coughing, and eye irritation (Lanzoni, 2023; Adiningsih & Hairuddin, 2021).

Individuals residing or working in buildings with inadequate indoor air quality may experience various symptoms, including headaches, eye irritation, fatigue, dry throat, sinus congestion, dizziness, and nausea. These symptoms can be caused by various illnesses, making the diagnosis of sick-building syndrome challenging (Tanir & Mete, 2022). Chemical pollutants (gas and vapour), emissions stemming from the products used in the building (like floor or wall covering, office equipment, furniture, insecticide, cleaning products), accidental spillage of chemicals and products used for construction purposes, adhesives, paints and combustion products such as carbon monoxide, formaldehyde, and nitrogen dioxide are included in this group and can cause nausea or vomiting if exceed the limit (Guagliardi *et al.*, 2022; Salari *et al.*, 2023; Samudro *et al.*, 2022; Babaoglu *et al.*, 2020). Some of the most harmful chemicals that are contained inside the buildings are CO, formaldehyde (HCHO) and total volatile organic compound (TVOC) (Samudro *et al.*, 2022). These types of pollutants are odourless, colourless gases and block the movement of oxygen in the body (Szabados *et al.*, 2022). It can have many effects depending on how much is breathed in (Salari *et al.*, 2023). It can affect coordination, worsen heart conditions, and cause extreme tiredness, headache, confusion, nausea, and dizziness (Tsantaki *et al.*, 2022).

A previous study revealed that the prevalence of dermal SBS among workers was relatively lower than in this study in different types of buildings, ranging from 11.9% to 15.9%, for dermal symptoms, compared to this study, which ranges from 9.1%-55.6% during SWM and 9.1%-55.6% for NEM at study area (Dhungana & Chalise., 2020). Dermal SBSS consists of scaling and itching besides skin rash and itchiness (Geng *et al.*, 2023; Surawattanasakul *et al.*, 2022). Other studies found a greater prevalence of weekly dermal (8.1% to 70.5%) in workplace building (Quoc *et al.*, 2020; Chang *et al.*, 2015). The high prevalence of SBS symptoms among workers in workplace settings could be influenced by multiple factors, including individual characteristics, working conditions, and building factors, especially indoor air quality.

Currently, most workers, ranging from 70 to 90%, are employed in industrial and indoor settings (Wang *et al.,* 2022Quoc *et al.*, 2022). Indoor air quality significantly impacts workers' health, especially sick building syndrome (SBS) symptoms (Dhungana & Chalise, 2020). Sick Building Syndrome (SBS) symptoms has emerged as a significant issue in public health and occupational settings because a majority of office workers spend around 90% of their working hours in indoor environments (Tsantaki *et al.*, 2022). The United States Environmental Protection Agency (U.S. EPA) coined the term Sick Building Syndrome (SBS) to refer to a medical condition where individuals in buildings exhibit unexplained symptoms or feelings of illness (Szabados *et al.*, 2022; Jeong *et al.,* 2021; Edimansyah., 2009). Sick Building Syndrome (SBS) symptoms is a collection of general symptoms such as headache, fatigue, and irritation of the upper respiratory tract, nose, throat, eyes, hands, and facial skin (Szalanski *et al.,* 2023; Cunningham *et al.*, 2022). The condition's intensity increases as the duration of individuals' stay in a building increases, and it improves or disappears when people exit the building (Ahmad *et al.*, 2023; Surawattanasakul *et al.*, 2022). SBS might appear in several work environments, including office buildings, factories, or other work structures (Dahari *et al.*, 2020; Choi *et al.*, 2020). Based on a report from the World Health Organisation (WHO), Sick Building Syndrome (SBS) has the potential to impact almost 30% of employees in newly constructed and refurbished buildings globally (Awada *et al.*, 2021; Cotta *et al.,* 2020). This can lead to substantial decreases in productivity, higher rates of employee absence, and more significant turnover among occupants, which are the factors that contribute to the risk of Sick Building Syndrome (SBS) (Anake & Nnamani., 2023; Azuma *et al.*, 2018). These factors include personal characteristics and working conditions, such as work-related stress, psychosocial issues, and allergy disorders (Maung *et al.*, 2022). Building-related factors also affect SBS (Lu *et al.*, 2018). Various building-related factors, such as insufficient HVAC systems, humidity, noise, indoor air pollutants (IAP) like particulate matter (PM), volatile organic compounds (VOCs), carbon monoxide (CO), formaldehyde, and carbon dioxide (CO_2), can all contribute to Sick Building Syndrome (SBS) (Tarragona *et al.*, 2024; Azuma *et al.*, 2018). While the causes of SBS may stem from multiple sources in this intricate setting, most of the risk factors are associated with indoor air quality (IAQ) (Salari *et al.*, 2023; Maung *et al.*, 2022; Choi *et al.*, 2020).

Trend of indoor air quality

This finding is consistent with the other studies from the tropical climate zones, including Malaysia (Fan & Ding, 2022; Lim *et al.*, 2015) and Taiwan (Chang *et al.*, 2015) which the finding of this study showed that there is the improvement of SBSS during the wet season (NEM) rather than dry monsoon (SWM) (Table 4.3) with the RH for each study area with range 72.92%-90.68% (S1), 57.77%-82.29% (S2), 68.25%-89.57% (S3), 69.15-71.2% (S4) for SWM and 76.13-86.04% (S1), 61.52-66.47% (S2), 67.37%-89.95% (S3), 67.19-71.6% (S4) for NEM and temperature at all sectors was in between 24ºC-32ºC. As recommended by ICOP IAQ 2010, indoor RH should be not lower than 40% and not more than 70%, and the acceptable ranges vary between 30% and 80% according to the IAQ standards in other East and Southeast Asian countries (Niza *et al.*, 2023; Zhu et al., 2021; Wahab *et al.*, 2015). Maintaining an indoor temperature between the range of 22-24°C and relative humidity of 40-60% is essential for ensuring adequate indoor air quality (IAQ) and minimising health issues such as headaches (Zhu *et al.*, 2024; Wolkoff *et al.*, 2021). Extreme high or low temperatures can impair work performance and elevate the likelihood of experiencing headaches and hoarse, dry throat (Tainio *et al.*, 2021; Selinheimo *et al.*, 2019). Raising the humidity level from 50% to 70% at temperatures of 26 and 30°C does not have a notable impact on physiological reactions, thermal comfort, perceived air quality, or symptoms of Sick Building Syndrome (SBS) (Chuang *et al.*, 2023). However, at 37°C, individuals experience increased heat sensation and discomfort and find it more challenging to accept the indoor air quality (Niza *et al.*, 2023). Optimal indoor humidity between 40% and 60%, combined with optimal room temperature, can improve health and work performance and reduce the risk of infection in office-like environments. However, high relative humidity of more than 80% can cause fatigue or lethargy among occupants besides increasing room temperature, especially in Asia with hot-humid climates (Byber *et al.*, 2021; Wolkoff *et al.*, 2021). Increasing relative humidity from 50% to 70% at 26 and 30°C did not significantly affect physiological responses (Szałański *et al.*, 2023). However, at 37°C and humidity, more than 80% of occupants felt hotter and more uncomfortable, making indoor air quality more difficult to accept (Zuo *et al.*, 2020). This situation showed that S1 and S3 have higher temperatures and relative humidity than S2 and S4. S1 and S3 had open ventilation, which used a fan and blower and open windows and door, while S2 and S4 had closed ventilation, which used centralised air conditioning. Open ventilation helps maintain a consistent temperature throughout your building and is mainly influenced by ambient air (Ahlawat *et al.*, 2020; Zhang *et al.*, 2021). Close vents in certain rooms those areas can become significantly hotter or colder than the rest of the building. This can create discomfort and lead to mould growth due to the lack of proper ventilation (Demanega *et al.*, 2021).

Many sources can cause formaldehyde (HCHO) inside the building. HCHO is found in three sub-economies: education (S1), wholesale and trade (S2), and boat-making manufacturing (S3). HCHO concentration for S1 is between 0.03-0.04 ppm for SWM and 0.018-0.020 ppm for NEM. The present HCHO comes from cabinetry and shelving made from pressed wood products that can emit formaldehyde (Fang *et al.*, 2022). This type of cabinet and shelve consists of the teacher's room. Paints, varnishes, and sealants use formaldehyde as a preservative, which can release the compound as it dries (Zin *et al.*, 2023; Zhang *et al*., 2021). During SWM, painting activities are conducted during sampling hours, which caused the measurement of HCHO to fluctuate. The concentration of HCHO at S2 is almost the same for both monsoonal seasons, consisting of 0.02-0.04 ppm during SWM and 0.02-0.03 ppm during NEM. HCHO concentration at S2 is contributed by cleaning products due to the reading of HCHO sparks when the cleaning activities were conducted around S2. Cleaning products and air fresheners may contain formaldehyde or formaldehyde-releasing agents (Huang *et al.*, 2020). S3 has HCHO fluctuation that started to spark when the workers at boat-making manufacturing started to combine the fibre and use glue, ranging from 0.010-0.014 ppm during SWM and 0.019-0.052 ppm during NEM. Many boat builders use composite materials containing formaldehyde-based resins, such as phenolic or urea-formaldehyde (Rajan & Rainosalo., 2023). These resins can release formaldehyde during and after the curing process, and certain adhesives and sealants used in boat construction and repair can contain formaldehyde or formaldehyde-releasing compounds (Nuryawan *et al.*, 2020). More orders for new boats and maintenance were conducted during NEM rather than SWM, which the director manager and workers in S3 have informed us.

Total volatile organic compounds (TVOC) were observed primarily in S3. The concentration of TVOC ranged from 0 to 6.5 parts per million (ppm) during the Southwest Monsoon (SWM) and from 0 to 0.19 ppm during the Northeast Monsoon (NEM). TVOCs, or Total Volatile Organic Compounds, are a significant problem in the boat manufacturing sector because of the potential release of these compounds into the air through different materials and procedures. TVOCs can be found in boat production because many boat-builders use polyester and epoxy resins. These resins can potentially release TVOCs during curing (Yang *et al.*, 2022). Gel coatings, which create a smooth and durable surface, can also include VOCs or Volatile Organic Compounds (Sersic, 2023; Mosallaei *et al.*, 2021). While not as prevalent, certain paints and varnishes may include formaldehyde or preservatives that release formaldehyde. In addition, several cleaning agents utilised during the boat manufacturing procedure may contain formaldehyde or compounds that release formaldehyde (Zin *et al.*, 2023; Sapuan *et al.*, 2022). Specific forms of insulation often employed in boats, such as fibreglass batt or foam board containing binders with formaldehyde, have the potential to emit formaldehyde gradually (Wang *et al.*, 2024).

Particulate matter or respirable suspended particles were quantified for all areas under study. The concentration of S1 is 0.038-0.050 mg/m^3 for SWM and 0.025-0.035 mg/m+ for NEM. The particle levels were elevated between 0830 and 0930 hours due to increased activity and movement within the teacher's room as the teachers prepared for instruction. S2 placed the RSP measurement within the range of 0.021-0.030 mg/m3 for SWM and 0.014-0.027 mg/m^3 for NEM. On the other hand, S3 positioned it within 0.04-0.134 mg/m^3 for SWM and 0.05-0.32 mg/m^3 for NEM. The most recent measurement for RSP at S4 ranged from 0.021 to 0.035 mg/m^3 using the SWM method and from 0.026 to 0.037 mg/m^3 using the NEM method. Resuspended particulate matter (RSP) originating from several sources, such as flooring, furniture, and carpets, can increase the levels of particulate matter (Alkaabi *et al.*, 2023). Additionally, dust and debris can accumulate in ventilation and air conditioning (HVAC) systems and circulate throughout the facility (Long *et al.*, 2023). This remark applies to all sites except housekeeping, where RSP can accumulate in the research area. When sanding and grinding composite materials such as fibreglass and carbon fibre, RSP can be released into the air. This can also occur when spray painting (Maung *et al.*, 2022). If the appropriate equipment or processes are not employed, the coatings have the potential to emit delicate particulate matter (Patel *et al.*, 2020). Boat interiors or construction using wood components can generate dust when cut, shaped, or finished (Zhang *et al.*, 2022). Manipulating foam materials for insulation or flotation can generate tiny particles, and cleaning procedures can cause dust to become airborne from surfaces or equipment (Krebs *et al.*, 2021). This statement supports a higher concentration level in the RSP at S3 compared to other study areas.

Higher exposure to CO_2 in office spaces or workplaces is moderately associated with some sick building syndrome symptoms, such as dry throat, tiredness, and dizziness, and lowering indoor CO_2 levels below 700 ppm can help reduce the risk of sick building syndrome among office workers, increase employee performance, productivity, and overall health (Niza *et al.*, 2023). Higher CO_2 concentrations are associated with increased perceived stuffy odour and skin SBS symptoms, while higher relative humidity reduces mucosal and skin SBS symptoms, but this benefit weakens with high CO_2 concentrations (Hou *et al.*, 2021). All CO_2 concentrations in the study area were under limit, and the highest CO_2 concentration was at S4 during SWM with 674.22 ppm. A CO_2 concentration of 400-1,000 ppm in indoor settings is considered acceptable (Taheri & Razban, 2021). This range is commonly used as a guideline for maintaining good indoor air quality in homes, offices, and public spaces. CO_2 is often measured in indoor environments to indicate quickly if additional ventilation is required (De Oliveira *et al*., 2019; Dai *et al.*, 2018). This study showed that ventilation was sufficient for the number of building workers. Increasing the number of occupants significantly impacts CO_2 production inside the buildings, requiring minimum outdoor ventilation rates to maintain good indoor air quality (Yalcin *et al.*, 2018), and this proves why S1 and S3 have lower CO_2 concentration due to their open ventilation rather than S2 and S4.

I/O ratio

The infiltration capacity for gaseous chemicals and smaller particles determines the I/O ratio, with higher values indicating more significant infiltration. Meteorology and turbulence are essential factors influencing indoor pollution conditions, as Alonso-

Blanco *et al.* (2023) stated. The indoor-outdoor ratio quantifies the difference between the concentration of a substance indoors and its corresponding concentration outdoors (Jeong *et al.*, 2021). I/O ratios of 1.2 or higher suggest that the concentration of indoor pollutants is higher than that of outside pollutants, and this difference can be attributable to sources within the indoor environment (Maskova *et al.*, 2020; Oh *et al.*, 2019). I/O ratios ranging from 0.8 to 1.2 suggest that the indoor concentration is comparable to the outdoor concentration. On the other hand, I/O ratios of 0.8 or lower show that the indoor concentration is lower than the outdoor concentration, indicating the potential influence of environmental factors (Alonso-Blanco *et al.*, 2023). The I/O ratio varies based on pollutants, with higher infiltration capacity for gaseous compounds and smaller particles, and meteorology and turbulence play key roles in influencing indoor pollution conditions (Alonso-Blanco *et al.*, 2023). The indoor-outdoor ratio assesses the disparity between the indoor concentration and the corresponding outdoor levels (Jeong *et al.*, 2021). The I/O ratios of 1.2 or greater indicate that the indoor concentration exceeds that of the outdoors and may be attributed to indoor sources (Maskova *et al.*, 2020; Oh *et al.*, 2019). I/O ratios of 0.8-1.2 indicate that the indoor concentration is equivalent to that of the outdoors, and I/O ratios of 0.8 or less indicate that the indoor concentration is less than that of the outdoors, illustrating the possibility of outdoor influence (Alonso-Blanco *et al.*, 2023; Alvino et al., 2018).

The I/O ratio suggested that indoor and outdoor air infiltration was comparable, except TVOC, which originated from indoor sources. The sources mentioned in the study conducted by Hu and Zhao (2020) encompassed resin, paint, paint thinner, and aldehydes, all of which were utilised in the manufacturing process of boats (Altendorf *et al.,* 2023). The input/output (I/O) ratios for S3 were 1.48 (NEM) and 1.52 (SWM), indicating that indoor sources in the research region are responsible for these values.

According to Krebs *et al.* (2021), if outdoor RSP concentrations increase by 10%, interior concentrations often increase by an average of 4.2-6.1% within 5 hours. The extent of this increase is affected by factors such as the age of the building and the prevailing climate conditions. Outdoor elements substantially impact indoor exposure to respirable suspended particles (RSP), and indoor air quality is also influenced by the chemical components present in HVAC systems (Xu *et al.*, 2020). The sources of RSP can originate from within the building. In this study, only the boat-making manufacturing sector (S3) in the sub-sector of manufacturing has an input-output ratio of more than 1.2 during both monsoonal seasons, precisely 1.38 during the SWM and 1.43 during the NEM. Sanding and grinding composite materials such as fibreglass and carbon fibre can release fine dust particles into the air (Yan *et al.,* 2022; Shrestha *et al.*, 2019). These particles can significantly source respirable suspended particles (RSP) inside buildings.

Throughout all monsoons, the level of carbon dioxide (CO_2) indoors was the same as the level outside, with an indoor-to-outdoor (I/O) ratio ranging from 0.92 to 1.14 for both monsoon variations in all research areas. (Zhu *et al.*, 2021). Individuals consistently release carbon dioxide through exhalation. Increased occupancy in space leads to elevated levels of carbon dioxide (CO_2), especially in regions with inadequate ventilation and insufficient air circulation inside the building (Paleologos *et al.*, 2021). Engaging in intense physical activity inside a limited area, such as exercising or breathing heavily, can elevate the concentration of carbon dioxide (CO_2) and establish it as the primary source of CO_2 within the structure (Angelova *et al.*, 2021). Insufficient ventilation can lead to carbon dioxide (CO_2) accumulation, mainly when there is restricted air exchange with the outside (Hattori *et al.*, 2022; Birmili *et al.,* 2021).

4.2.2 Simulation of Computational Fluid Dynamics

In the simulation you describe, several key observations can be made about the airflow and ventilation dynamics within the study area building, including fresh air distribution, velocity changes, velocity and pressure gradients, and turbulence (Bhatti *et al*., 2020; Barbosa & Brum, 2018). The introduction of fresh air through the inlet causes it to circulate and mix with the air already present in the room, which includes air exhaled by the occupants (Fernandez *et al*., 2023; Pei & Rim, 2021). This circulation is depicted by vectors indicating airflow velocity and direction, showing how the fresh air spreads throughout the room. The velocity decreases as the airflow moves from the inlet towards the outlet. This is a common phenomenon in ventilation systems where the airflow slows down due to various factors such as friction with surfaces, changes in direction, or mixing with other air masses (Marashian *et al.*, 2023).

At a cut plane near the ventilation fan, there are noticeable gradients in both velocity and pressure. This suggests that the airflow experiences significant changes in speed and pressure as it passes through this area, likely due to the influence of the fan, which creates a high-pressure zone and accelerates the airflow (Goodarzi *et al.*, 2023). The contour map of turbulent kinetic energy at this cut plane reveals high turbulence near mechanical ventilation. Turbulent kinetic energy measures the turbulence intensity in the airflow (Filho *et al.*, 2021). High turbulence near the fan indicates that the air is mixing vigorously, typical around mechanical ventilation systems, as they introduce and disperse air rapidly (Capua *et al.*, 2023; Kochkov *et al.,* 2019). In summary, the simulation shows how fresh air is distributed and mixed within the room, how the airflow velocity changes as it moves through the room, and how the mechanical ventilation system generates turbulence (Bousiotis *et al*., 2023; Canha *et al.*, 2021). The observed pressure, velocity gradients, and high turbulence near the fan indicate the complex dynamics in ensuring adequate ventilation in varying conditions.

Both monsoons, which include SWM and NEM, suggest that the simulation accounts for different seasonal or weather conditions affecting the room's ventilation. The high turbulence observed for both monsoon conditions implies that the mechanical ventilation system is dealing with significant variability in airflow due to external factors like wind or temperature changes. The simulation accuracy for SWM was 91.9% for S1, 77.75% for S2, 88.06% for S3, and 89% for S4. The simulation accuracy for NEM was 89.57% for S1, 70.64% for S2, 86.62% for S3, and 91.17% for S4. Validate the model by comparing its results with experimental data or analytical solutions and choose relevant benchmarks for the specific problem (Nakora *et al.*, 2020). Refine the model for RSP parameters, air movement and boundary conditions based on comparison results to improve accuracy (Fermo *et al.*, 2021). Use error percentages and convergence criteria to assess how well your model fits the experimental data based on the nature of data in the study area (Bousiotis *et al.*, 2023).

4.2.3 Principal Component Analysis (PCA) as source apportionment

The data set must have an acceptability or adequacy score of more than 0.5 to proceed with Principal Component Analysis (PCA) (Greenacre *et al.*, 2022). The KMO results indicate that the data meets this requirement. Bartlett's test yielded a statistically significant p-value of less than 0.05 ($p\text{-value} < 0.05$), precisely 0.00 (Beattie *et al.*, 2021; Kherif & Latypova, 2020). Both tests demonstrated that all data sets met the Principal Component Analysis (PCA) criteria. The KMO and Bartlett's Test values are provided for all sites. The KMO and Bartlett's Test values meet the requirement for Principal Component Analysis (PCA), as shown in Table 4.6. The KMO Test yielded a range of 0.440 to 0.702, indicating that all sites demonstrated sufficient data adequacy. Results from source apportionment analysis consist of 3 principal components (PCs) consisting of physical condition and inadequate ventilation, physical activities, and chemical exposure for all study areas.

Physical condition and inadequate ventilation

Indoor air temperature (T) and relative humidity (RH) are crucial for maintaining good indoor air quality (IAQ). Managing indoor conditions is especially important in Terengganu, where outdoor air is cold (NEM) and dry (SWM). Indoor humidity is often higher than outdoor levels due to moisture sources inside buildings. This can increase moisture loads on building materials. Adequate ventilation removes excess humidity and temperature and maintains good IAQ. Municipal buildings with higher occupancy need more ventilation than fewer occupant buildings to manage CO_, incredibly open ventilation (S1, S3), and closed ventilation (S2, S4). Managing indoor temperature and humidity effectively is essential for comfort, health, and building integrity, especially in the variables in SWM and NEM.

The assessment of indoor air quality (IAQ) often relies on measuring the concentration of CO_2 inside the space. The current concentration of CO_2 in the ambient air ranges from 300 to 700 parts per million (ppm), as reported by Branco *et al.* (2019), Telejko and Zender-Swiercz (2016), and Sireesha (2017). The content of carbon dioxide (CO_2) inside the room grew due to the presence of occupants and gas equipment, which are familiar sources of CO_2. The amount of carbon dioxide (CO_2) produced by people inside a structure is influenced by their physical activities, the effectiveness of the building's ventilation system, their health condition, food, and other factors (Subri *et al.,* 2024; Mainka *et al.*, 2018; Telekjo & Zender-Swiercz, 2016). The concentrations of CO_2 were naturally in direct proportion to the number of occupants. Insufficient supply of air movement can result in stagnant CO_2 concentration within the building (Zender *et al.*, 2019). This aligns with the results presented in Table 4.12. The principal components analysis (PCA) revealed a strong correlation between air movement and CO2 concentrations across the study area, indicating a significant link between these variables. The relationship between CO_2 and AM is observed in the principal components PC-1 during the monsoonal season at S1, with a contribution of 31.389%. In addition, PC-1 during the Southwest Monsoon (SWM) at S2 has a contribution of 22.635%, PC-3 during the Northeast Monsoon (NEM) at S2 has a contribution of 19.071%, PC-1 for both SWM (37.790%) and NEM (42.583%) at S3, and PC-2 (23.231%) for SWM and PC-1 (28.523%) for NEM at S4 (Table 4.8-4.12).

Physical activities- Respirable particulates

Depending on where the respirable particulate, also known as respirable suspended particulate (RSP), comes from, indoor particle pollution is divided into primary and secondary RSP. Primary indoor pollutants are produced directly by home interior activities like sanding, housekeeping, faxing, photocopying machines, smoking tobacco, cleaning, and other indoor tasks based on the building activities (Sani *et al.*, 2021). Pollutants seep into the building from the outside world, and particles produced by chemical interactions between indoor and outdoor sources are examples of secondary RSP (Zhang *et al.*, 2021). Additionally, human activity in the rooms or spaces may cause dust resuspension or RSP, especially for S2 and S3 for both the monsoonal season and S1 (NEM). PC-3 (NEM) S1; PC-3(SWM), PC-1(NEM) for S2; PC-3 (SWM) for S3; PC-2 (NEM), PC-1(SWM) S4. RSP is emitted from paints, cleaning agents, and air fresheners, and VOCs can interact with other substances to form fine particles. Specific chemical reactions within the indoor environment can produce secondary particulate matter. These events result in PCs forming in RSP and other chemicals such as PC-1 (SWM) in S4, PC-2 (NEM) in S3, and PC-2 in S1 during SWM. The contribution of these chemicals is 31.415% (Table 4.11), 65.453% (Table 4.10), and 17.873% (Table 4.8), respectively.

Chemical exposures

The chemical exposure was classified based on various chemical pollutants in all research sites, including HCHO, TVOC, CO, and RSP. TVOC stands for total volatile organic compound concentration in the air. Formaldehyde is a distinct VOC with its characteristics and health hazards (Suwanaruang, 2023; Susanto *et al.,* 2021). Simultaneously monitoring both factors can offer a holistic perspective on indoor air quality and the possible dangers it poses to health (Huang *et al.*, 2020). Indoor formaldehyde (HCHO) can originate from wood furniture that contains adhesives with formaldehyde. Additionally, it can be produced within buildings through chemical reactions and combustion processes (Shrestha et al., 2019; Chen *et al.*, 2018; Salthammer, 2019). Enhancing airflow and decreasing the number of people in recently built university dorms can enhance the quality of the air inside, thus supporting the health and well-being of the occupants. The citation is from Sarna et al in 2022. Carbon monoxide (CO) is an invisible and scentless gas that can pose a risk when it builds indoors (Saini *et al.*, 2020). Carbon monoxide is generated through the incomplete burning of fuels that contain carbon. Common indoor sources of carbon monoxide include fuel-burning equipment like gas stoves and ovens. If these items are not correctly adjusted or are malfunctioning, they can release carbon monoxide (Jung *et al.*, 2023; Kakoulli *et al.,* 2022). The presence of carbon monoxide (CO) was detected only at S1. This was caused by the residents cooking within the instructors' quarters, contributing to the CO levels. The indoor air quality in buildings in Seoul, Korea, typically exhibits elevated levels of pollutants due to several chemical processes and insufficient ventilation. Buildings located near roadways experience even greater levels of pollutants due to the dispersion of these substances (Altendorf *et al.*, 2023; Kakoulli *et al.*, 2018; Yang *et al.*, 2015). This demonstrates that various actions conducted within the structures might produce chemical exposure within the structures. The findings of this study are consistent with the results of a previous study. Each pollutant (HCHO, TVOC, CO, and RSP) was grouped into the same categories called PCs. For example, PC-2 was associated with S1 during SWM (17.873%) and NEM (18.919%), PC-2 was associated with SWM (22.635%) and NEM (19.866%) at S2, and PC-2 was associated with both monsoons at S3, with percentages of 24.169% (SWM) and 22.870% (NEM). PC-2 has a share of 23.231% in the SWM category and 24.642% in the NEM category for S4.

4.2.4 Prediction of Indoor Air Quality and Sick Building Syndrome

The study used various statistical methods to analyse the data, revealing that it did not follow a normal distribution. Initially, the Kolmogorov-Smirnov test confirmed this non-normality with a p-value less than 0.05, leading to the rejection of the null hypothesis of normality (Rodriguez, 2020; Jain & Mandowara, 2019). Consequently, an ANOVA was performed to investigate differences in air pollutant levels across stations, showing significant differences with a p-value of 0.000. Given the non-parametric nature of the data, the Kruskal-Wallis test was employed as an alternative to ANOVA (Kiurski *et al.*, 2019). This test assessed differences across multiple samples under the null hypothesis of homogeneity with stochastic heterogeneity (Rayner & Livingston, 2020). For model selection, the Akaike Information Criterion (AIC) was used to evaluate the relative quality of different models, with lower AIC values indicating better models (Anuar *et al.*, 2021; Duris, & Tirpáková, 2020). An omnibus test was conducted to determine any overarching effects in the data (Yan *et al.*, 2022; Tozzi *et al.*, 2020; Portet, 2020). In contrast, the likelihood ratio chi-squared test was used to compare nested models across two distinct datasets: the southwest monsoon (SWM) and the northeast monsoon (NEM).

GLM model with Gamma distribution showed that SBSS is related to indoor air quality. Each symptom contributes to physical and chemical performance indicators based on ventilation performances in the study area and activities conducted inside the building. The fluctuation of temperature and relative humidity in each research area and the chemical exposures resulting from the activities undertaken within the study area are the reasons for this phenomenon. The three critical parameters for assessing good indoor air quality (IAQ) are air movement (m/s), indoor relative humidity (%), and indoor air temperature (°C). These factors evaluate people's comfort level within a building (Ma *et al.*, 2021). A further critical issue is the level of airtightness in the building envelope. The optimal temperature indoors ranges from 20 to 22 °C (Kakoulli *et al.*, 2022; Elshawi *et al*., 2019). Temperatures ranging from 23 to 26 °C are often considered comfortable in hot weather (Ma *et al.*, 2021). However, most study sites were consistently above this threshold throughout the SWM period. An optimal indoor climate is characterised by a temperature ranging from 18 to 24 °C (Wei *et al.,* 2022; Wang & Norbäck, 2021). Extreme temperature fluctuations can pose a risk to human well-being and result in headaches (Qabbal *et al.*, 2022). Extreme temperatures and improper humidity levels can contribute to an environment where SBS symptoms are more likely to occur (Sani *et al.,* 2021). Factors such as poor ventilation, inadequate temperature and humidity control, and indoor pollutants can all affect occupants' health and comfort. SBSS that occur due to poor indoor quality due to temperature and relative humidity are headache, feeling heavy-headed, fatigue or lethargy, drowsiness, dizziness, nausea or vomiting, cough, hoarse or dry throat, skin rashness and irritation of the eye (Ma *et al.*, 2021; Samsuddin *et al.*, 2018).

TVOCs have irritant properties and can adversely affect respiratory health, leading to symptoms such as headaches, dizziness, weariness, eye irritation, hoarseness or dryness of the throat, and skin rashes (Borowski *et al.*, 2022). Formaldehyde (HCHO) is classified as a volatile organic compound (VOC) and is recognized for its irritating solid properties. Prolonged or chronic exposure to formaldehyde can result in symptoms such as headaches, dizziness, nausea or vomiting, exhaustion, and irritation of the eyes, skin, and respiratory system (Reda *et al.*, 2022). (Yang *et al.*, 2023). The occupant is the primary contributor to indoor air pollution through inhaling pollutants emitted by the occupant (Tran *et al.*, 2019; Scibor *et al.*, 2019; Samsuddin *et al.*, 2018). HCHO is generated through natural processes, although its global yearly production already surpasses 20 million (Heim *et al.*, 2017). Formaldehyde (HCHO) significantly contributes to indoor and outdoor air pollution. Outdoor sources of formaldehyde (HCHO) can originate from the atmospheric interaction of volatile organic compounds (VOCs), the biosphere, fuel combustion, biomass burning, and transportation (Cong *et al.*, 2019; Liu *et al.*, 2019; Salthammer, 2019). Indoor formaldehyde (HCHO) can be present in wood furniture constructed using formaldehyde adhesives. Formaldehyde can also be produced within buildings through chemical reactions and combustion processes. Research has indicated that outdoor formaldehyde (HCHO) significantly contributes to indoor pollution (Concilio *et al*., 2024; Chen *et al*., 2018; Salthammer, 2019). Outdoor formaldehyde (HCHO) is a contributor to indoor pollution, along with other sources within buildings. This is mainly caused by releasing pollutants from powerful emission sources (Liu *et al*., 2019; Chen *et al*., 2018).

Numerous investigations revealed a correlation between human dry eye, headache, feeling heavy-headed, dizziness, nausea, and cough due to indoor contaminants, especially CO_2 (Yang *et al.*, 2023; Conceicao *et al*.,2018). Furthermore, toxicological studies demonstrated that the primary pathogenic mechanisms behind ocular surface illnesses include oxidative damage, disruption of tight junctions, and chronic inflammation brought on by indoor pollution. CO_2 concentration in indoor air pollution was high, caused by accumulation from indoor sources such as formaldehyde and other volatile compounds. These compounds lead to several health effects and symptoms on occupants, common headaches, loss of concentration, absenteeism, and fatigue (Fu et al., 2022; Chen *et al.*, 2018). Besides that, low IAQ can increase the risk of people who have breathing problems, such as asthma sufferers or those with undeveloped immune systems, which mostly occurs among workers (Gialelis *et al.*, 2023; Piscitelli *et al*., 2022; Branco, 2018). CO_2 concentration inside the room is widely used as one of the criteria for assessing indoor air quality (IAQ). Contents of CO_2 in atmospheric air currently range from 300- 700 ppm (Branco *et al.*, 2019; Telekjo and Zender-Swiercz., 2016; Sireesha., 2017). The concentration of CO_2 increased inside the room with living organisms and gas equipment as typical sources. The level of CO_2 released by building occupants depends on the physical activities of the occupants, health conditions, diet, etc. (Mainka *et al.*, 2018; Telekjo and Zender-Swiercz., 2016). Concentrations of CO_2 naturally were directly proportional to the number of occupants, and the make-up air supply was too low, depending on its concentration in the outdoor air (Laurent et al., 2021; Zender *et al.*, 2019). The concentration of CO_2 caused this in the exhaled air of people, and the allowable indoor CO_2 concentration was 1000ppm for current IAQ standards (Mainka *et al.*, 2018; Qiu *et al.*, 2019; Telejko *et al.*, 2016). 1000ppm usually defined as maximum concentration of CO_2 in case of mechanical ventilation controlled by CO_2 sensors (Zender-Swiercz and Telekjo., 2019; Ferdyn-Grygierek *et al.*, 2019). Higher exposure to CO_2 and total VOCs in office spaces is moderately associated with some symptoms of sick building syndrome, such as dry throat, tiredness, and dizziness, and lowering indoor CO_2 levels below 700 ppm can help reduce the risk of sick building syndrome among office workers (Niza *et al.*, 2023; Latif *et al.*, 2018; Morawska *et al.*, 2017).

It is commonly recognized that indoor RSP levels are significantly influenced by ambient (outdoor). The chemical makeup and disease burden of indoor RSP are significantly influenced by several other factors, such as indoor types of homes, offices, and commercial spaces; ventilation arrangements (naturally provided by windows or mechanical ventilation); occupancy rate and time; endotoxin levels; and geographic location (Braun *et al.*, 2019). Microfibers released by weathering over time significantly negatively impact human lungs when inhaled and cause the formation of RSP (Drago *et al.*, 2018). RSP sources are caused by human habits, including opening windows often and engaging in other dust-producing indoor activities (Alvino *et al.*, 2018). Human walking is a significant contributing component to indoor resuspension because it exposes human soles to the air while they are moving and can cause many SBSS such as headache, drowsiness, dizziness, fatigue of lethargy, skin rashness and irritation of eyes (Piscitelli *et al.*, 2022; Zhang *et al.*, 2021). Variations in temperature between indoor and outdoor spaces also alter natural ventilation by causing air to move, affecting the concentration of RSP indoors (Qiu *et al.*, 2019). The rate at which RSP reduced as relative humidity increased (Ji *et al.*, 2021). The higher the air exchange rate, RSP concentration inside was generally lower (Shaw *et al.*, 2024). Seasonality is one crucial component affecting indoor RSP distribution (Chattopadhyay & Shaw., 2021; Jain & Mandowara, 2019). The concentration of RSP inside is influenced by building type and season. Compared to the NEM, SWM RSP concentration was noticeably greater (Han *et al.*, 2015). According to epidemiological data from industrialized and developing countries ' areas, compared to wet and dry seasons (Li *et al.*, 2024), there is a sharp increase in airborne RSP throughout the SWM (wet) and NEM (dry). There are monsoonal variations in the RSP distribution due to meteorological parameters such as wind speed, precipitation, soil and air temperature, and soil and atmospheric humidity (Kumar et al., 2023; Islam et al., 2021).

The optimal model for a gamma distribution is chosen by evaluating the accuracy of parameter estimates, conducting goodness-of-fit tests, and considering model selection criteria such as AIC (Khalid & Sarwat, 2021). Visual inspections conducted through plots and robustness tests serve to verify that the gamma distribution accurately represents the data. In addition, performance indicators, comprising error and accuracy measures, were utilized to identify the most suitable model, and the findings were consistent with the AIC value (Usman *et al.*, 2022). The characteristics of the data, such as its distribution shape, sample size, presence of outliers, and quality, can all impact the fit and accuracy of the gamma distribution model (Jimenez *et al.*, 2021; Han et al., 2015). Thorough evaluation of these parameters and the meticulous selection and validation procedures guarantee that the gamma distribution model is the most accurate representation of the data (Gurmach *et al.*, 2022). Choosing the most suitable SBSS model between SWM and NEM is crucial based on this method. The fitted model for SWM consists of feeling heavy- headache (S1, S4), fatigue and lethargy (S1), drowsiness (S1, S3), dizziness (S2, S3), nausea and vomiting (S3), cough (S1, S2), hoarse or dry throat (S1, S3), skin rashness and itchiness (S3, S4), irritation of eye (S1, S3).

The study highlights the performance of the Gamma Model in forecasting Sick Building Syndrome (SBS) symptoms during two different monsoon periods: the Northeast Monsoon (NEM) and the Southwest Monsoon (SWM). The analysis shows that the Gamma Model, particularly during NEM, demonstrated superior predictive capabilities compared to the SWM model for most symptoms related to SBSS. The performance indicators used in the study, including RMSE, MAE, NAE (error measures) and R^2, IA (accuracy measures), all point to the NEM model being more effective in reducing errors and improving accuracy. The low error rates in RMSE, MAE, and NAE during NEM, combined with higher R^2 and IA values, demonstrate the ability of the model to closely predict the observed outcomes (Correndo *et al.,* 2021). For example, Site 1 for headache showed an RMSE of 2.201 and R^2 of 0.742, which are significantly better than the SWM model. Similarly, for other symptoms like dizziness and nausea, NEM outperformed SWM with considerably lower errors and higher accuracy rates. In specific cases, the error reduction was remarkable, particularly for dizziness and skin rash, where NEM reduced errors by 15.49% and 57.70%, respectively (S1). The accuracy improvement was also significant, with dizziness improving by 86.70% and skin rash by 86.45%. These metrics indicate the robustness of the NEM model in forecasting SBS symptoms under varying indoor environmental conditions, influenced by air pollutants and other factors during the NEM.

The study also proved the importance of variable selection and model screening before applying the Gamma Model (Dunder *et al.,* 2018). The approach of using screening methods and selecting relevant variables enhanced the predictive performance of the NEM model, helping it deal with multivariate data sets and correlated variables more effectively. By addressing collinearity and improving the goodness of fit, the Gamma Model during NEM could capture the relationships between indoor air pollutants, ventilation, and SBS symptoms more accurately. However, despite its success in reducing multicollinearity and improving the model's fit, the study acknowledges that the Gamma Model still has limitations in fully mitigating multicollinearity due to the complexity of factors affecting dependant variables such as in this study SBS symptoms, such as physical and chemical air pollutants and ventilation performance indicators (Nardino *et al*., 2022). Nevertheless, the NEM model was able to provide more degrees of freedom and deliver reliable forecasts.

In the comparison of the two monsoons, it is evident that the NEM model is more successful in predicting symptoms like headache, fatigue, dizziness, nausea, and skin rash. The influence of factors like temperature, relative humidity, and air pollutants is likely more pronounced during NEM, which could explain the model's better performance during this period. The findings suggest that the environmental conditions during NEM have a stronger impact on SBSS, leading to better model accuracy. Interestingly, the SWM model was not without merit. For some symptoms like drowsiness, cough, and irritation of the eye, the SWM model demonstrated increased accuracy, with improvements up to 82.85% for hoarse or dry throat. This suggests that while NEM generally performed better, the SWM model is still relevant for specific SBS symptoms.

The study successfully demonstrates that the NEM model is better equipped to predict SBS symptoms under the given conditions. By reducing errors and improving accuracy, especially for key symptoms like headache, dizziness, and skin rash, the NEM model proves to be a more effective forecasting tool for SBS symptoms compared to SWM. This highlights the importance of selecting appropriate models based on environmental conditions and the specific variables influencing health outcomes within indoor environments. The improved predictive ability of the Gamma Model during NEM reinforces the need for detailed variable screening and collinearity management in air quality studies, as it enhances the accuracy and reliability of the forecasts. These findings can inform future research and interventions aimed at mitigating SBS symptoms, particularly in regions affected by varying monsoon season.

The implementation of the Gamma model significantly enhanced its predictive ability, particularly during the NEM model, due to its capacity to handle multivariate datasets with highly correlated variables (Franklin *et al*., 2020; Kozama *et al*., 2018; Lengyel *et al*., 2004). This study employed the Gamma model to forecast daily air quality, demonstrating that appropriate imputation techniques can yield robust predictive models (Tran *et al.,* 2018; Rashid *et al*., 2017). The selection of variables in the model helped mitigate collinearity issues, reducing the number of predictors and enhancing model performance. However, despite these advantages, the Gamma model could not entirely eliminate multicollinearity, particularly concerning factors influencing Sick Building Syndrome (SBS) symptoms, such as physical and chemical air pollutants and ventilation performance indicators (Abdullah *et al.,* 2020; Deng *et al*., 2020). Nevertheless, the Gamma model's ability to address multi-collinearity issues and provide more degrees of freedom made it a valuable tool in this context (Tran *et al*., 2018).

This study explored the comparative effectiveness of the NEM and Southwest Monsoon (SWM) models in forecasting SBS symptoms influenced by indoor air pollutants. It was found that the NEM model generally outperformed the SWM model in predicting SBS symptoms due to its superior handling of factors like temperature, relative humidity, and air pollutants during the NEM period. The NEM model notably reduced the error rates for symptoms such as headaches (34.63%), fatigue or lethargy (20.97%), drowsiness (38.75%), nausea or vomiting (4.06%), hoarse or dry throat (40.57%), skin rash or itchiness (2.39%), and eye irritation (10.29%). Conversely, the SWM model demonstrated better performance in reducing errors for symptoms such as feeling heavy-headed (8.78%), dizziness (10.76%), and cough (31.55%).

The performance indicators highlighted that the NEM model could significantly increase accuracy, with notable improvements such as 47.36% for headaches, 66.72% for fatigue or lethargy, 42.07% for drowsiness, 33.29% for nausea or vomiting, 74.47% for hoarse or dry throat, 19.97% for eye irritation, and 2.94% for skin rash or itchiness. Similarly, the SWM model showed substantial accuracy improvements for symptoms like drowsiness (64.20%), cough (58.54%), hoarse or dry throat (82.85%), and eye irritation (46.48%). These findings underscore the models' ability to enhance predictive accuracy and reduce errors in SBS symptom forecasting.

The study demonstrated that both the NEM and SWM models contributed to improved accuracy in SBS symptom prediction, with each model excelling in different symptom categories. Specifically, the Gamma model during the SWM period achieved accuracy rates of 42.67% for feeling heavy-headed, 9.55% for dizziness, and 71.97% for cough, as detailed in Table 4.34. These results affirm the Gamma model's effectiveness in increasing predictive accuracy and reducing errors across various SBS symptoms, highlighting its applicability in different monsoonal contexts for IAQ forecasting. The comprehensive analysis and comparative results between the NEM and SWM models provide valuable insights into optimizing predictive models for better management of IAQ-related health outcomes.

CHAPTER 5

CONCLUSION AND RECCOMENDATIONS

5.1 Conclusion

In conclusion, the study areas' air pollutants and physical parameters fluctuated over time. The mean concentration of physical parameters showed incompliances for temperature 27.62-30.4^{0}C (S1, SWM), 26.84- 29.58^{0}C (S1, NEM), 27.62- 29.93^{0}C (S2, SWM), 25.98- 27.43^{0}C (S2, NEM), 27.12-32.91^{0}C (S3, SWM), 27.28- 32.4^{0}C (S3, NEM), 24.20- 25.36^{0}C (S4, SWM), and 23.5-24.2^{0}C (S4, NEM), while relative humidity higher with 72.92-90.68% (S1, SWM), 76.13-86.04% (S1, NEM), 57.77-82.29% (S2, SWM), 6152-66.47% (S2, NEM), 68.25-89.57% (S3, SWM), 67.37-89.95% (S3, NEM), 69.15- 71.2% (SWM, S4) and 67.19-71.6% (NEM, S4). The relative humidity and temperature trend was inversely proportional in all study areas. Most workers attributed their symptoms over the past three months and current symptoms to their workstations. Specifically, 90.9% (n=10, S1) and 66.7% (n=22, S2) of workers reported symptoms during both the monsoonal season, while 68.75% (n=11, SWM, S3) and 44.4% (n=8, SWM) reported symptoms during the SWM season. Additionally, 81.25% (n=13, NEM, S3) and 33.3% (n=6, NEM, S4) of workers reported symptoms during the Northeast Monsoon season. All of these workers answered "Yes" when asked, “This is due to the environment of the workstation?”. Most of the workers experience relief from the symptoms “After leaving the workplace” for SK Tanjung Gelam (S1), TMG Mart (S2) workers were feeling relief from the symptoms with answer “After leave building” with 72.7% (n=24), 27.3% (n=9) answered “After building, Mset Inflatable Composit Corporation Sdn. Bhd (S3) showed that most of the workers stated that they relief with the answers “After leave workplace” with 50% (n=17, SWM, S1), 62.5% (n=62.5%, NEM, S1) and Raia Hotel (S4) workers believed that they feel relief when they leave the workplace, the answer “After leave workplace” with 55.6% (n=10). The symptoms occur mostly during lunch or evening, and not sure of the study areas.

Spatial data analysis reveals that the airflow velocity direction aligns with the room's streamlines. During the investigation, it was observed that the airflow passed through the layout of the study area (S1-S4) and traveled towards the outlet, which might be windows or doors for open ventilation (S1 & S3) or the outlet of mechanical ventilation for closed ventilation. The shape of airflow velocity is at a cut plane near the ventilation, which is the air conditioning or fan. Around the mechanical ventilation, significant pressure and velocity gradients in the air were noted. The contour of turbulent airflow kinetic energy is shown at the cut plane. The vicinity of the mechanical ventilation was found to have high turbulent kinetic energy for both monsoons. The accuracy of the simulation for SWM at the study area was 91.9% (S1), 77.75% (S2), 88.06% (S3), and 89% (S4), while for NEM, the accuracy of simulation (R^2) was 89.57% (S1), 70.64% (S2), 86.62% (S3) and 91.17% (S4).

The PCA analysis revealed that the primary contributors to poor indoor air quality (IAQ) were the physical condition of the environment and insufficient ventilation. These factors encompass many physical characteristics, such as relative humidity, temperature, and air movement, as well as indicators of ventilation performance, such as CO_2 levels. The second cause of indoor air pollution was chemical parameters within the building primarily comes from physical activities. These activities directly generate indoor pollutants, such as sanding, housekeeping, faxing, photocopying, smoking tobacco, cleaning, and other indoor duties. In addition, human activity in the rooms or spaces can lead to the suspension of dust particles or RSP, particularly in S2 and S3 during both the monsoonal season and S1 (NEM). PC-3 (NEM) is used for S1. PC-3 (SWM) and PC-1 (NEM) are used for S2. PC-3 (SWM) is used for S3. PC-2 (NEM) and PC-1 (SWM) are used for S4. Chemical exposure was identified as the third component based on the presence of different chemical pollutants at all research site and for most of the places chemical parameters were categorized as PC2, including HCHO, TVOC, CO, and RSP. The air quality indoors in buildings across all sectors of the economy generally shows increased levels of pollutants due to various chemical reactions and inadequate ventilation. Buildings near roadways are subject to heightened levels of pollutants due to the dispersion of these substances. Each pollutant, including formaldehyde (HCHO), total volatile organic compounds (TVOC), carbon monoxide (CO), and respirable suspended particulates (RSP), was classified into the same categories referred to as principal components (PCs). PC-2 exhibited associations with S1 during SWM (17.873%) and NEM (18.919%). At S2, PC-2 was related to SWM (22.635%) and NEM (19.866%). At S3, PC-2 was associated with both monsoons, with percentages of 24.169% (SWM) and 22.870% (NEM). PC-2 holds a 23.231% market share in the SWM category and 24.642% in the NEM category for S4.

The development of Gamma models revealed the range of R^2 between 0.10 (headache, S3) to 0.964 (irritation of eye, S1) for SWM. The R^2 for SWM ranged from 0.4014 (drowsiness, S1) to 0.9949 (dizziness, S1), and after validation, the most outperforming model was SWM with validation of R2 ranged from 0.329 to 0.495, which is higher compared to NEM model 0.002 to 0.295. In general, SWM model is able in reducing the error of models by 13.64% (Drowsiness, S1), 12.26% (cough, S1), 2.53% (Hoarse dry throat, S1), 61.67% (irritation of eye, S1), 8.78% (Feeling heavy headed, S2), 10.76% (Dizziness, S2), 31.55% (Cough, S2), 23.13% (Drowsiness, S3), 61.85% (Dizziness, S3), 33.38% (Nausea or vomiting, S3), 23.68% (Hoarse or dry throat, S3), 21.32% (skin rash or itchiness, S3), 64.62% (Irritation of eyes, S3), 37.65% (Feeling heavy headed, S4), 49.02% (Hoarse or dry throat, 49.02, S4), 27.54% (skin rashness and itchiness, S4) and 22.50% (Irritation of eye, S4) which same goes with NEM that outperform SWM such as 10.68% (Headache, S1), 2.90% (Feeling heavy headed, S1), 6.81% (Fatigue or lethargy, S1), 15.49% (Dizziness, S1), 13.51% (Nausea or vomiting, S1), 57.70% (Skin rashness or itchiness, S1), 34.63% (Headache, S2), 20.97% (fatigue or lethargy, S2), 38.75% (Drowsiness, S2), 4.06% (Nausea or vomiting, S2), 40.57% (Hoarse or dry throat, S2), 2.39% (Skin rashness or itchiness, S2), 10.29% (Irritation of eyes, S2), 22.76% (Headache, S3), 33.22% (Feeling Heavy Headed, S3), 27.89% (Fatigue or lethargy, S3), 85.40 (Cough, S3), 33.88% (Headache, S4), 38.02% (Fatigue or lethargy, S4), 38.26% (Drowsiness, S4), 36.59% (Dizziness, S4), 22.21% (Nausea or vomiting) and 13.85%, (Cough, S4). In conclusion, this study proved that the NEM model was the best-fitted model for each site for certain SBS symptoms. The most suitable model for a gamma distribution is selected by assessing the accuracy of parameter estimations, performing goodness-of-fit tests, and considering model selection criteria such as AIC. Inspections conducted through plots and robustness tests confirm the accuracy of the gamma distribution in representing the data. Furthermore, performance metrics, including error and accuracy measures, were used to choose the most appropriate model, and the results were consistent with the AIC value.

5.2 Recommendations

This study specifically examined the economy of the Terengganu subsector, focusing on the region's dominant sub-sector and its impact on indoor air quality (IAQ). However, future studies could be conducted on a broader scale to enhance or expand the current research scope. Expanding the research geographically and across different sub-sectors would provide a more comprehensive understanding of IAQ issues. This broader approach would involve collecting data from various regions within Terengganu and extending the study to other states or countries. Such geographical diversity would help capture regional variations in IAQ, offering insights into how different environmental and socio-economic conditions influence air quality.

Sub-sector expansion could also be included in future studies, covering industrial, residential, commercial, and institutional sectors. This inclusive approach would ensure the model used in the research captures the full spectrum of IAQ issues across different environments. By incorporating a wider range of data points, researchers could create models that learn from a more diverse and representative sample of real-world conditions. This diversity is crucial for developing accurate predictive models that can identify patterns, trends, and exceptions, enhancing their reliability. Large datasets allow models to detect subtle patterns and correlations that might be overlooked in smaller datasets. By understanding these intricate relationships between various IAQ parameters and external factors, researchers could develop more precise mitigation strategies.

Regarding data collection for Sick Building Syndrome (SBS) symptoms, this study initially used questionnaires requiring respondents to report SBS symptoms over three months. This method, however, posed a risk of providing inaccurate predictions due to its reliance on a single time frame. Future research should consider periodic data collection from the same respondents to achieve more accurate model predictions. Periodic data collection would capture the variability in SBS symptoms, which can fluctuate due to changes in environmental conditions, building maintenance, or personal health. This approach would allow for longitudinal analyses, tracking symptom progression over time and identifying trends or patterns that cross-sectional data might not reveal.

The study also highlighted the use of the Gamma model within the GLM framework for modelling continuous, skewed positive-valued data. While the Gamma model is useful, it has limitations, such as its inability to handle zero values, sensitivity to outliers, issues with overdispersion, and challenges in parameter estimation and interpretation. Future studies should address these limitations by considering the data characteristics and exploring alternative modelling approaches or robust statistical techniques. Enhancing the Gamma Distribution GLM could involve its application to more diverse IAQ datasets, including multi-zone buildings and varied categorical datasets. Additionally, future research could explore adaptations of the Gamma Distribution GLM to handle complexities like time series data and spatial variability, improving its predictive performance.

Lastly, this study recommends several measures to improve indoor air quality across all study areas, such as enhanced housekeeping practices, effective source control, and optimized ventilation systems. By focusing on these strategies, future research can contribute to developing practical solutions for maintaining healthy indoor environments, reducing the prevalence of IAQ-related health issues, and improving overall well-being in various settings.

Housekeeping practices

Inadequate housekeeping can significantly contribute to indoor air quality (IAQ) problems, making it essential to maintain a clean workplace to promote a healthy indoor environment. Good housekeeping practices are pivotal in preventing and resolving many IAQ issues, as a clean workspace reduces the accumulation of dust, allergens, and harmful chemicals. The implementation of the 5S technique such as sorting, setting in order, straightening, simplifying, shining, and systematic cleaning which can standardize housekeeping efforts across various workplace sectors, ensuring a consistent and effective approach to cleanliness. This method not only improves the physical organization of the workplace but also enhances air quality by reducing clutter that can harbour dust and pollutants.

Minimizing furnishings such as racks and cabinets, along with properly enclosing storage areas for waste, particularly scheduled waste, can further reduce chemical exposure and prevent the accumulation of trapped dust. Open storage solutions are less effective in containing dust and fumes, whereas closed storage helps in maintaining a cleaner environment. Additionally, ensuring that windows are opened during working hours in areas with open ventilation can significantly improve natural airflow, aiding in the removal of indoor pollutants. In spaces where open ventilation is not feasible, installing and optimizing mechanical ventilation and air conditioning (MVAC) systems is crucial to maintaining adequate air exchange and filtration.

Switching from conventional detergents to eco-friendly cleaning chemicals can also play a significant role in reducing chemical exposure for occupants during housekeeping activities. These eco-friendly alternatives are designed to minimize the release of volatile organic compounds (VOCs) and other harmful substances into the air, thereby enhancing overall IAQ. Moreover, limiting the use of chemicals such as resins, adhesives, paints, cleaning agents, and those involved in combustion processes like vehicles inside the workplace is vital. By controlling and restricting these substances, workplaces can prevent high concentrations of harmful chemicals from accumulating in the air.

Adequate ventilation is necessary to dilute any remaining chemical concentrations, ensuring that fresh air can circulate, and pollutants are effectively dispersed. In addition to these measures, it is essential to minimize workers' direct exposure to chemicals by providing appropriate personal protective equipment (PPE), such as gloves, masks, and goggles. This protective gear serves as a barrier against harmful substances, reducing the risk of health issues related to chemical exposure. Regular inspection and timely replacement of PPE ensure its effectiveness and reliability in protecting workers.

By integrating these strategies can improving housekeeping practices, enhancing ventilation, using eco-friendly cleaning products, restricting hazardous chemicals, and equipping workers with proper PPE which workplaces can create a safer and healthier environment for employees. These efforts not only contribute to better IAQ but also promote the overall well-being of the workforce, reducing the incidence of work-related health problems and fostering a more productive and pleasant workplace.

Source control

Source control focuses on eliminating individual sources of pollutants or reducing their emissions and is generally the most effective strategy for improving IAQ. The best prevention method involves avoiding the introduction of unnecessary contaminants into the workplace, such as cigarettes and harmful chemicals. When the use of certain chemicals is unavoidable, it is crucial to provide adequate ventilation to mitigate potential hazards. Source removal involves preventing pollutant sources from entering the workplace or minimizing their use. This can include measures like banning smoking within the workplace or restricting access to hazardous chemicals unless absolutely necessary.

Source substitution is another vital aspect of source control, which involves replacing polluting materials with eco-friendly or nontoxic alternatives. For example, using low-VOC paints, biodegradable cleaning agents, and safer adhesives can significantly reduce the emission of harmful substances into the indoor environment. Additionally, reducing the number of workers in each workspace or limiting the duration of activities involving chemical use can lower exposure to pollutants and indirectly decrease CO_2 concentrations. Fewer workers or shorter exposure times mean fewer emissions, contributing to improved air quality.

Increasing the rate of ventilation is essential in removing accumulated chemicals and CO_2 from indoor spaces. Ventilation enhancements such as installing ceiling fans, exhaust fans, tornado turbines, or roof ventilators are necessary measures to increase the exchange of indoor air with outdoor air. These devices help to expel stale air laden with pollutants and bring in fresh air, diluting the concentration of harmful substances. By implementing such ventilation solutions, workplaces can ensure a more consistent flow of fresh air, effectively reducing indoor pollutant levels and maintaining healthier air quality for occupants. These combined efforts of source control, substitution, and enhanced ventilation create a comprehensive strategy to minimize indoor air pollution and promote a safer, healthier working environment.

Ventilation system

In a hot and humid country like Malaysia, consisting of different monsoonal variations, such as the southwest monsoon (SWM) and northeast monsoon (NEM), a building needs suitable ventilation for workers to work in a thermally comfortable environment. Therefore, for existing workplaces, especially in critical areas such as industrial and heavy traffic areas, mechanical ventilation, such as air conditioning, must be installed to ensure a conducive and comfortable working environment. Good maintenance of mechanical ventilation inside the workplace can maintain indoor air quality. For the construction of a new factory or workplace, it is recommended that the Department of Safety and Health, in collaboration with the Department of Environment, provide more detailed guidelines for buffer zones. This is particularly important for areas related to chemical exposure, which can lead to environmental pollution. Guidelines should include measures for controlling air pollution, such as using air pollution control (APC) systems, which must be stricter to manage the dispersion of polluted air.

The reliance on energy-dependent ventilation or cooling mechanisms for achieving good IAQ in the workplace can be extremely costly, as suggested, and may still be insufficient. For this reason, any plan to minimize energy consumption needs to improve overall IAQ in the workplace. This may consist of simple measures such as more strategic urban planning and enforcement of each category that places the gazette as an industrial, commercial, residential, or commercial area. Smarter windows design and placements that encourage higher air exchange, ventilation, and velocity or use alternative building materials that do not trap heat or induced pollutants indoors.

It is very expensive to install and maintain a very good ventilation system and a very fine material in a building. Still, it is no waste, and there is nothing wrong with doing it, especially with the importance of good indoor air, and it is also worth spending with. The health and comfort of the workers are dominant factors that contribute to the workers' productivity in the workplace, which in turn affects performance and achievement. Furthermore, a reliable indicator of air quality is crucial for ensuring a conducive working environment, especially for workers, who are among the country's most valuable assets.

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Referred Articles in Journal (Accepted and Published)

1. **Mansor, A. A**., Abdullah, S., Ahmad, A. N., Ahmed, A. N., Zulkifli, M. F. R., Jusoh, S. M., & Ismail, M. (2024). Indoor air quality and sick building syndrome symptoms in administrative office at public university. *Dialogues in Health*, *4*, 100178.
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3. **Mansor, A. A.,** Abdullah, S., Dom, N. C., Ahmed, A. N., & Ismail, M. (2022). Investigating the Indoor and Outdoor Respirable Suspended Particulates of Coarse (PM_{10}), Fine ($PM_{2.5}$) and Ultrafine (PM_1). Malaysian Journal of Medicine & Health Sciences, 18.
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5. **Mansor, A. A**., Abdullah, S., Napi, N. N. L. M., Ahmed, A. N., & Ismail, M. (2022). Diurnal trend of particulate matter concentration at industrial area using multivariate analysis. *Journal of Sustainability Science and Management*, *17*(3), 132-144.
6. **Mansor, A. A.,** Abdullah, S., Dom, N. C., Napi, N. N. L. M., Ahmed, A. N., Ismail, M., & Zulkifli, M. F. R. (2021). Three-Hour-Ahead of Multiple Linear Regression (MLR) Models for Particulate Matter (PM_{10}) Forecasting. *Int. J. Des. Nat. Ecodyn, 16*, 53-59.

Conference Proceedings

1. **Mansor A.A**., Abdullah S., Ahmad Nawawi M.A., Ahmed A.N., Mohd Napi N.N.L., Ismail M. (2023). Investigating Indoor Air Quality (IAQ) and Sick Building Syndrome Symptoms (SBSS) using generalized linear model. Healthscope: The Official Research Book of Faculty of Health Sciences, UiTM
2. **Mansor**, A.A., Abdullah, S., Ahmad, A.N., Ismail, M (2022). Spatio-Temporal Analysis of Indoor Air Quality (Iaq) In Different Micro-Environments. 1st Ocean Pollution and Ecotoxicology Symposium (OPECS 2022)
3. **Mansor A.A**., Abdullah S., Ahmad Nawawi M.A., Ahmed A.N., Mohd Napi N.N.L., Ismail M. (2020). Temporal and Spatial Analysis of the Occupational Noise at Rice Mill in Kedah IOP Conference Series: Earth and Environmental Science,
4. **Mansor,** A.A., Hisham, A.N.B., Abdullah, S., Napi, N.N.L.M., Ahmed, A.N., Ismail.M. (2020). Indoor-Outdoor Air Quality Assessment in Nurseries. IOP Conference Series: Earth and Environmental Science, 616.

APPENDIX A

Questionnaire for Building Occupants

This short questionnaire has been given to you to facilitate the identification of potential sources of indoor air quality (IAQ) pollutants and to identify adverse health effects that may be associated with exposure to these pollutants. Your answers will remain confidential. Please complete the form as accurately as possible before returning to us.

Date:

General information

1. Building/Company name :
2. Department/Division :
3. Has your Company carried out any assessment related to IAQ?

☐ Yes ☐ No ☐ In progress ☐ Not sure

Background factor

1. Sex ☐ Male ☐ Female
2. Age ☐ <25 year ☐ 25-39 year ☐ 40-55 years ☐ >55 0years
3. Do you smoke? ☐ Yes ☐ Sometimes ☐ No

Nature of Occupation

1. Occupation/Position :
2. How long you have been at your present place of work? yr(s) mth(s)
3. No. of hours spent per day at your main workstation : hr(s)

Environmental Conditions

1. Type of workstation: ☐ Enclosed room ☐ Open concept
2. How is your area air-conditioned? ☐ Central unit ☐ Local Unit (Split Unit)
3. No. of people sharing your workstation:
4. Please indicate if you work with or near the following equipment:

	Everyday	2-3 times weekly	Never
a) Typewriter	☐	☐	☐
b) Video display unit/computer	☐	☐	☐
c) Photocopier	☐	☐	☐
d) Fax machine	☐	☐	☐

5) Have you been bothered during the last three (3) months by any of the following factors at your workstation/workplace?

	Yes, often (every week)	Yes, sometimes	No, never
a) Draught	☐	☐	☐
b) Room temperature too high	☐	☐	☐
c)Varying room temperature	☐	☐	☐
d)Room temperature too low	☐	☐	☐
e) Stuffy "bad" air	☐	☐	☐
f) Dry air	☐	☐	☐
g) Unpleasant odour	☐	☐	☐
h) Passive smoking	☐	☐	☐
i) Dust and dirt	☐	☐	☐

Symptoms
Past symptoms

	Yes	No
a) Have you ever had asthmatic problems?		
If yes, during last year?		
b) Have you ever suffered from sinusitis?		
If yes, during last year?		
c) Have you ever suffered from eczema?		
If yes, during last year?		

Present Symptoms

1. During the last three (3) months, have you had any of the following symptoms at work (Answer every question even if you have not had any symptoms)

	Yes, often (every week)	Yes, sometimes (2-3 times/week)	No, never	If yes, do you believe that is due to your work environment? Yes	No
a) Headache					
b)Feeling heavy-headed					
c)Fatigue/ lethargy					
d)Drowsiness					
e)Dizziness					
f)Nausea/vomiting					
g)Cough					
h)Irritated, stuffy nose					
i)Hoarse, dry throat					
j)Skin rash/ itchiness					
k)Irritation of the eyes					
l)Scaling/itching scalp or ears					

2. No. of days in the past one (1) month that you had to take off work because of this symptom:
___________________ day(s)

3. When do these symptoms occur?
   - ☐ Mornings
   - ☐ Afternoons
   - ☐ No noticeable trend

4. When do you experience relief from these symptoms?
   - ☐ After I leave my workstation
   - ☐ After I leave the building
   - ☐ No noticeable trend

5. If female, are you currently pregnant?
   - ☐ Yes
   - ☐ No
   - ☐ Not sure

Correlation Analysis

		Present symptoms									
	S1 (SWM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught										0.621*
	Room temperature too high										
	Varying room temperature										
	Room temperature too low										
	Stuffy bad air	0.671*									
	Dry air						0.216*		0.930*		
	Unpleasant odour									0.838**	0.723*
	Passive smoking										
	Dust and dirt										0.649*

		Present Symptoms									
	S1 (NEM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught										
	Room temperature too high										
	Varying room temperature										
	Room temperature too low										
	Stuffy bad air	0.854*						-0.782**	0.641*		
	Dry air		0.621*								0.647*
	unpleasant odour									0.838**	0.723*

	Passive smoking										
	Dust and dirt										0.649*

		Present Symptoms									
	S2 (SWM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught		0.396*								
	Room temperature too high		0.450**								
	Varying room temperature										
	Room temperature too low										
	Stuffy bad air		0.463**								
	Dry air									0.742*	
	Unpleasant odour							0.347*			
	Passive smoking				-0.552**						
	Dust and dirt										

		Present Symptoms									
	S2 (NEM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught		0.408*								
	Room temperature too high		0.474**								
	Varying room temperature								0.351*		
	Room temperature too low			0.450**	0.418*		0.424*				
	Stuffy bad air										

		Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
	Dry air	0.269*								0.463*	
	Unpleasant odour										
	Passive smoking				0.452**						
	Dust and dirt										

		Present symptoms									
	S3 (SWM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught								0.545*		
	Room temperature too high										
	Varying room temperature										
	Room temperature too low	0.552*								0.585*	0.516*
	Stuffy bad air			0.500*							
	Dry air									0.371*	
	Unpleasant odour			0.539*						0.651**	
	Passive smoking										
	Dust and dirt										

		Present symptoms									
	S3 (NEM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught								0.545*		
	Room temperature too high										
	Varying room temperature										

		Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
	Room temperature too low	0.552*								0.585*	0.516*
	Stuffy bad air			0.500*							
	Dry air										
	Unpleasant odour			0.539*						0.651**	
	Passive smoking										
	Dust and dirt										

		Present symptoms									
	S4 (SWM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month symptom	Draught										
	Room temperature too high										
	Varying room temperature										
	Room temperature too low										
	Stuffy bad air										
	Dry air	-0.273									
	Unpleasant odour										
	Passive smoking								-0.581*		
	Dust and dirt				-0.559*						

		Present symptoms									
	S4 (NEM)	Headache	Feeling heavy headed	Fatigue lethargy	Drowsiness	Dizziness	Nausea vomiting	Cough	Hoarse dry throat	Skin rash itchiness	Irritation of the eye
Past 3-Month	Draught										
	Room temperature too high			0.526*		-0.600**					-0.573*

Varying room temperature	0.516*		
Room temperature too low	-0.553*		
Stuffy bad air			
Dry air			
Unpleasant odour	-0.645**		
Passive smoking		-0.591**	
Dust and dirt			-0.485*