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Impact of Haze Event on Daily Admission of Respiratory System Patients in Peninsular Malaysia

(Impak Jerebu terhadap Kemasukan Harian Pesakit Sistem Pernafasan Di Semenanjung Malaysia)

Nurul Anis Ayuni Khairul Anuar, Humaida Banu Samsudin & Noriza Majid*

Mathematical Science Department, Faculty of Science and Technology, Universiti Kebangsaan Malaysia, 43600 UKM Bangi, Selangor, Malaysia

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ABSTRACT

Diseases of the respiratory system, especially in children and the elderly, are significantly related to air pollution. Exposure to air pollution has led to an increase in the number of patients who need hospital treatment. The purpose of this study was to learn about the effects of changes in the levels of major pollutant components on the number of daily hospital admissions of respiratory system patients. The generalised linear lag model is used in this study to demonstrate the lag structure of the exposure-response impacts. The results show that particulate matter (PM_{10}), nitrogen dioxide (NO_2), carbon monoxide (CO), and ozone (O_3) component factors, as well as meteorological factors like wind speed and ultraviolet (UV) radiation, affect the number of hospital admissions of respiratory system patients. The best model is a lag 6 negative binomial regression model. Daily hospital admission is positively correlated with PM_{10}, NO_2, and wind speed, and negatively correlated with CO, O_3, and UV radiation. According to the findings of the study, fine particulate matter ($PM_{2.5}$) and sulphur dioxide (SO_2), as well as temperature, humidity, and wind direction, are not significantly contributing factors in the number of respiratory system patients admitted to hospitals.

Keywords: Air pollution; generalised linear lag model; hospital admissions; negative binomial regression; respiratory system diseases

ABSTRAK

Penyakit sistem pernafasan, terutamanya pada kanak-kanak dan orang tua mempunyai kaitan yang ketara dengan pencemaran udara. Pendedahan kepada pencemaran udara telah menyebabkan peningkatan bilangan pesakit yang memerlukan rawatan di hospital. Tujuan kajian ini adalah untuk mengetahui tentang kesan perubahan tahap komponen pencemar utama terhadap kekerapan kemasukan ke hospital harian pesakit sistem pernafasan. Model lag linear teritlak digunakan dalam kajian ini untuk menunjukkan struktur lag bagi kesan pendedahan-tindak balas. Keputusan menunjukkan bahawa partikel terampai (PM_{10}), nitrogen dioksida (NO_2), karbon monoksida (CO), dan faktor komponen ozon (O_3), serta faktor meteorologi seperti kelajuan angin dan sinaran UV, mempengaruhi bilangan kemasukan pesakit sistem pernafasan ke hospital. Model terbaik ialah model regresi binomial negatif lag 6. Kemasukan hospital harian berkorelasi positif dengan PM_{10}, NO_2, dan kelajuan angin, dan berkorelasi negatif dengan sinaran CO, O_3, dan ultraviolet (UV). Menurut penemuan kajian, partikel terampai halus ($PM_{2.5}$) dan sulfur dioksida (SO_2), serta suhu, kelembapan, dan arah angin, bukan merupakan faktor penyumbang yang signifikan terhadap kemasukan pesakit sistem pernafasan ke hospital.

Kata kunci: Kemasukan hospital; model lag linear teritlak; pencemaran udara; penyakit sistem pernafasan; regresi binomial negatif

INTRODUCTION

Globally, respiratory diseases have emerged as a leading cause of death and disability (Marciniuk et al. 2014; Murray & Lopez 1996). As described by the Ministry of Health Malaysia (MOH) (2021), diseases of the respiratory system are those that cause difficulty exchanging oxygen and carbon dioxide in the lungs and the airways. It can affect some structures and organs related to breathing including the nasal cavity, pharynx or throat, larynx, trachea, bronchus, bronchioles, lung tissue and respiratory muscles of the chest ribs (Hansen-Flaschen 2022). In Malaysia, respiratory illnesses are among the top three reasons for hospitalisation and mortality (MOH 2021). The percentage of patients admitted to public and private hospitals in 2019 with respiratory system diagnoses was 13.26% and 18.55%, respectively (MOH 2020). In the same year, it was cited as a factor in 21.17 percent of deaths at government hospitals and 15.57 percent of deaths at private hospitals. This has made diseases of the respiratory system the second leading cause of death, after cardiovascular diseases (21.8%) by a factor of 20.65 percent.

According to the Forum of International Respiratory Society (FIRS) (2021), acute lower respiratory tract infections have risen to prominence as a major cause of morbidity and mortality in both young and old people. Children under the age of five and people over the age of 65 account for an estimated 2.4 million annual deaths as a result of this. Pneumonia is one of the most common lower respiratory tract infections, with the highest global health impact. Pneumonia, as defined by Otieno, Joseph and John (2012), is an inflammation of the alveoli brought on by an infection in the lungs. Pustules and fluid in the alveoli prevent the normal exchange and intake of oxygen, making breathing difficult. United Nations Children's Fund (UNICEF) (2022) reports that there are more than 1,400 cases of pneumonia for every 100,000 children in the world in the year 2022. South Asia has the highest reported prevalence, at 2,500 cases per 100,000 children (UNICEF 2022). Kulkarni et al. (2022) found that there were as many as 738 thousand pneumonia-related hospitalisations of children younger than five years old around the world in 2019. In the same year, 740,180 young children died as a direct result of pneumonia. This represents 14% of all deaths in this age group (WHO 2021).

In 2019, there were a total of 145,419 cases of pneumonia and 7,542 deaths in Malaysia (Mohd Diah & Aziz 2021). Department of Statistics Malaysia's (DOSM) (2020) data show that pneumonia is the leading cause of death for women in Malaysia, accounting for 12.8% of all female deaths. In 2021, we can expect the same thing to happen. According to data from DOSM (2021), pneumonia is responsible for the second-highest death rate in the country, behind ischemic heart disease. There were 13,851 deaths directly attributable to it, or 11.4% of all deaths.

Chronic respiratory disease (CRD) has been identified as the predominant global contributor to disease burden and premature mortality rates, as supported by the research conducted by Hanafi et al. (2021) and Bousquet and Khaltaev (2007). In terms of chronic respiratory diseases, asthma and chronic obstructive pulmonary disease (COPD) are frequently observed as the prevailing conditions. Numerous chronic respiratory diseases have a significant global impact, affecting a substantial population exceeding one million individuals. Among these diseases, asthma and chronic obstructive pulmonary disease (COPD) stand out as the most prevalent conditions (World Health Organisation, 2008). According to Naser et al. (2021), there has been a 2.5% rise in hospitalisations related to chronic obstructive pulmonary disease (COPD) because of exposure to these pollutants. According to MOH (2020), there has been a significant rise in the prevalence of respiratory diseases, specifically asthma, by 15.8%, from 1,187 to 1,375. According to Santos et al. (2021), the elderly population is more prone to experiencing acute cases and hospitalisations related to chronic respiratory diseases when they are exposed to pollutants. Furthermore, Santos et al. (2021) discovered a significant correlation between the exposure of children to PM_{10}, $PM_{2.5}$, and NO_2 and the increased incidence of hospital admissions attributed to asthma. Based on the outcomes of Othman et al. (2014), it was observed that the influence of smoke haze on inpatient rates exhibited the greatest magnitude among children, followed by young adults, senior citizens, and infants. Based on these previous studies, it can be concluded that there is a positive correlation between the rise in air pollution levels and the increased incidence of respiratory illnesses.

The study conducted by Othman et al. (2014) examined the health impacts associated with transboundary haze pollution in the region of Kuala Lumpur and its adjacent areas in Selangor during the periods of 2005, 2006, 2008, and 2009. The findings shown is a significant rise of 31 percent in the number of inpatient cases attributed to illnesses related to the haze, compared to days with normal air quality. Another study conducted at Universiti Kebangsaan Malaysia Medical Centre (UKMMC) indicated a significant difference in hospital admissions during periods with haze as compared to those without haze (Ming et al. 2018). The number of hospital admissions shows a twofold increase during the period of haze and a significant increase in patients' requiring admission to the intensive care unit. Furthermore, the length of hospital stays during periods of haze is approximately twice longer during periods without haze. Previous research conducted in Malaysia has primarily concentrated on the scientific aspects of air pollution, with limited attention given to the economic impacts resulting from the adverse health effects caused by haze

(Othman et al. 2014). Hence, the primary aim of this study was to assess the short-term impact of air pollutants and meteorological variables on the number of daily incidence of hospitalisations associated with respiratory diseases. The important aspect of this health impact assessment lies in its ability to enhance our understanding of the magnitude of transboundary haze hazards in relation to public health issues.

METHODS

The dataset used in this study was obtained from the Health Informatics Centre in the Planning Division of the Ministry of Health Malaysia. It includes information on the total number of daily admissions of patients with respiratory system diseases across all 92 government hospitals located in Peninsular Malaysia, categorised by state. The Department of Environment (DOE) of the Ministry of Environment and Water, provides information regarding various air pollutants, including SO_2, NO_2, CO, O_3, PM_{10}, and $PM_{2.5}$. Also, the DOE provides data on meteorological variables such as wind direction, wind speed, relative humidity, ultraviolet radiation, and temperature. The data collected includes the average concentration of individual pollutants present in the atmospheric environment across all states within Peninsular Malaysia. The provided dataset encompasses the transboundary haze incident that occurred in Malaysia during the four-month period from June 1st to September 30th in the year 2019. Haze occurrences have been recorded almost every year from June to September since 2005, mainly on the central west coast of Peninsular Malaysia (Latif et al. 2018).

Table 1 displays the distribution of patients with respiratory system diseases who were admitted to government hospitals in Peninsular Malaysia throughout the haze period, which covers from June to September. During the specified time frame, a total of 242,276 individuals were admitted to hospitals in Peninsular Malaysia because of respiratory system diseases. During the months of June and July, Johor experienced a significant surge in daily cases, with recorded figures of 490 and 528, respectively. Selangor recorded the highest number of daily cases during the months of August and September, with 462 and 412 cases reported, respectively. During the period from June to July, several states in Peninsular Malaysia witnessed a notable rise in hospital admissions, which was subsequently followed by a decline from August to September.

TABLE 1. Daily patient admissions to MOH Hospitals in Peninsular Malaysia by state during the haze period (June-September)

State	June			July			August			September		
	Min	Average	Max	Min	Average	Max	Min	Average	Max	Min	Average	Max
Johor	170	367	490	352	434	528	234	352	462	220	327	424
Selangor	130	314	464	271	405	522	214	330	456	194	290	378
Perak	148	209	272	162	207	248	126	192	252	168	204	264
Kedah	106	187	244	148	202	262	126	176	215	142	172	206
Pahang	104	154	192	94	155	218	108	140	176	96	134	170
Kelantan	76	138	186	98	147	190	96	133	175	90	128	180
Negeri Sembilan	84	132	176	100	146	196	64	121	158	64	117	176
Melaka	68	122	192	94	136	186	72	108	142	82	109	140
Kuala Lumpur	78	109	148	68	123	168	76	107	154	52	104	150
Penang	40	106	176	74	110	144	60	99	148	70	97	134
Terengganu	44	96	168	48	108	144	54	97	150	62	91	136
Perlis	16	32	50	12	32	46	20	35	48	20	32	46
Putrajaya	4	18	40	6	21	32	8	21	32	6	17	28

Table 2 presents the average values of pollutant components and meteorological factors during the haze season in Peninsular Malaysia. The air quality measurements above 100 g/m^3 indicated the highest levels for the PM_{10} component, with a reading of 164.37 g/m^3, and the $PM_{2.5}$ component, with a reading of 151.72 g/m^3. The period stretching from June to September recorded an average daily temperature of 28.27 °C.

The Air Pollutany Index (API) reading is commonly determined by the concentration of fine dust, which constitutes PM_{10} and $PM_{2.5}$. This pollutant is typically the most prevalent, particularly during events of haze in Malaysia (DOE 2006). Since 1997, the average levels of PM_{10} and $PM_{2.5}$ particles observed during episodes of haze consistently exceeded the levels observed during non-haze periods (Latif et al. 2018). Since 2017, the $PM_{2.5}$ component has been employed as a benchmark for determining measurements of the API. Therefore, the $PM_{2.5}$ component readings of each state in Peninsular Malaysia were utilised to determine the states that were included in this study. Based on the data presented in Table 3, it can be observed that Penang exhibits the highest levels of $PM_{2.5}$, falling within the range of 101 to 200. Subsequently, Putrajaya, Negeri Sembilan, Kuala Lumpur, Selangor, Melaka, Perak, and Pahang follow suit in terms of $PM_{2.5}$ levels. The states selected for this study were those that exhibited higher levels of $PM_{2.5}$ pollution, as previously mentioned.

Previous studies have employed a generalised linear regression model approach, encompassing Poisson, quasi-Poisson, and negative binomial models with a non-linear lag distribution model, to examine the association between the mentioned pollutants and daily hospital admissions of patients (Atkinson et al. 1999; Chen, Mengersen & Tong 2006; de Souza et al. 2014; Gabriella, Abdullah & Soemartojo 2019; Jin et al. 2022; Santos et al. 2021; Seyoum, Ndlovu & Zewotir 2016). The primary objective of statistical regression modelling is to evaluate the impact of a group of predictors on a specific outcome. When there are delayed effects in the dependency, the situation becomes more complicated.

TABLE 2. Descriptive statistics for air pollutant components and meteorological factors in Peninsular Malaysia during haze season (June-September)

Variables	Min	Average	Max
Air Pollutant Components			
PM_{10} (μg/m^3)	7.75	41.19	164.37
$PM_{2.5}$ (μg/m^3)	4.90	31.85	151.72
O_3 (ppb)	4.86	20.60	45.01
NO_2 (ppb)	1.51	8.40	26.63
SO_2 (ppb)	0.15	1.15	3.37
CO (ppb)	0.32	0.70	1.83
Meteorological Factors			
Temperature (°C)	24.05	28.27	35.09
Humidity (%)	59.15	79.96	95.85
Wind direction (°)	35.34	154.33	233.73
Wind Speed (m/s)	0.53	1.17	2.86
Solar Radiation (W/m^2)	43.78	333.24	554.60

TABLE 3. $PM_{2.5}$ Components (g/m³) During the Haze Season (June-September) in Peninsular Malaysia

State	Min	Average	Max
Johor	7.76	30.01	151.72
Selangor	7.64	41.51	145.39
Perak	8.49	38.07	141.36
Kedah	11.08	41.44	136.97
Pahang	11.64	40.45	136.88
Kelantan	9.75	36.10	135.12
Negeri Sembilan	8.93	29.80	107.26
Melaka	9.10	32.39	103.54
Kuala Lumpur	7.76	28.99	100.45
Penang	7.14	25.92	97.23
Terengganu	5.35	23.44	84.99
Perlis	5.83	24.69	82.98
Putrajaya	4.90	21.31	62.85

Specifically, an exposure event or a specific instance of a predictor can continue to influence the outcome even after the specified duration has passed (Gasparrini 2011). Lag-involved models are frequently employed by researchers to examine the impact of pollution on human health (de Souza et al. 2014; Gasparrini, Armstrong & Kenward 2010; Jin et al. 2022). Jin et al. (2022) found that there exists a temporal lag between air pollution exposure and subsequent respiratory hospital admissions, with the observed impact surfacing within a time frame of less than 7 days. In this study, we employed a generalised linear regression model to investigate the impact of lag (ranging from lag 0 to lag 7) on daily variations in average air pollutant levels and hospitalisations related to respiratory system diseases in specific states. This particular model is often found in research studies that investigate the relationship between air pollution and respiratory diseases. The reason for its acceptance is that it takes into account both the immediate and prolonged effects of exposure to pollution. A linear predictor, also known as a linear function regressor (McCullagh & Nelder 1989), is used in the regressive linear model:

$$\eta_i = \beta_0 + \beta_1 X_{1,i} + \cdots + \beta_k X_{k,i} \tag{1}$$

The relation between random and systematic components as defined by a link function:

Poisson Model	quasi-Poisson Model	Negative Binomial Model
$E(Y) = \mu$ $Var\ (Y) = \mu$	$E(Y) = \mu$ $Var\ (Y) = \emptyset\mu$	$E(Y) = \mu$ $Var\ (Y) = (1 + \theta\mu)$

$$g(\mu_i) = \eta_i = \ln \mu_i = x_i'\beta$$
$$\mu_i = g^{-1}(\eta_i) = g^{-1}(x_i'\beta) = e^{x_i'\beta}$$
$$Y_i = g^{-1}(\eta_i) + \varepsilon_i \quad (2)$$
$$\ln \mu_i = \beta_0 + \beta_1 X_1 + \cdots + \beta_k X_k$$

The following equation describes the generalised linear model:

$$\ln \mu_i = \beta_0 + \beta_1 X_1 + \beta_2 X_2 + \cdots + \beta_k X_k + \gamma_1 D_{i,1} + \gamma_2 D_{i,2} + \cdots + \gamma_k D_{i,k} \; ; \; \mathrm{i} = 1,2,3,\ldots,\mathrm{n} \quad (3)$$

where μ_i is the number of hospital admissions for respiratory system at i day and X_1, X_2,..., X_k represent pollution and meteorological factor variables whilst $D_{i,1}$, $D_{i,2}$, ..., $D_{i,k}$ stands for a state in Peninsular Malaysia with an unhealthy air pollutant index (API) reading above 101. This study focuses on the states of Penang, Putrajaya, Negeri Sembilan, Kuala Lumpur, Selangor, Melaka, Perak and Pahang due to their high levels of API pollution.

Maximum likelihood (MLE) method and the generalised linear model (GLM) link function were used to estimate the model parameters (Cameron & Trivedi 2013). Stepwise regression was used to determine the statistical significance of each independent variable in the linear regression model. Diagnostic tests should be performed to ensure that the data collected meets the linear model's assumptions, as follows: a) the relationship between the dependent and independent variables is not linear, b) correlations between independent variables are low, c) the dependent variable does not follow a normal distribution (the distribution is from the exponential family i.e., binomial, poisson, multinomial), d) the model is heteroskedastic with variance uniformity not necessarily satisfied, and e) errors are independent but not normally distributed.

The process of identifying the most suitable regression model for this dataset requires the application of model fitting techniques. This study employs the generalised linear lag model for presenting data derived from the Poisson, quasi-Poisson, and negative binomial regression models. In order to adjust for any lag effect, the readings of air pollutants on the current day (lag0) and the previous seven days (lag1–7) were incorporated into the model. The time lag model with the most favourable performance was chosen based on the minimum *p*-values (Jin et al. 2022). To control for any lag effect, incorporated into the model. The best time lag model was selected according to the minimum *p* values; only models with a single lag were taken into consideration. A significance level of $p < 0.05$ was established for all analyses. The Spearman correlation coefficient was employed to assess the associations between the air pollutants and meteorological factors. Variance inflation factor (VIF) is used to identify the presence of multicollinearity within the independent variables. The log likelihood value, Akaike's Information Criterion (AIC), the Bayesian Information Criterion (BIC), and a derived deviance test are all factors that will be considered in the selection of an appropriate model.

Results and Discussions

The results of model evaluation tests are summarised in Table 4 for the three types of regression models (lag0 - lag7). The lag 6 model displayed the best. Upon carrying out an analysis of the log likelihood, AIC, BIC, and deviance measures for all models, it was determined that the lag 0 model exhibits the highest level of preference. However, most of prior research employed a lag-structured model to assess the impact of pollution exposure on hospitalisations, incorporating a delayed effect (de Souza et al. 2014; Gasparrini, Armstrong & Kenward 2010; Jin et al. 2022). The incident of hospitalisation has been estimated to take place several days after exposure to pollution. The varying impacts of individual pollution components on the human body are based upon the level of exposure. Typically, the emergence of severe symptoms which requires hospitalisation occurs within a few days. The patient's hospitalisation timeline is influenced by both the severity of their health condition and the pollutant component reading. Using a lag 0 model in this investigation would be deemed inappropriate. Given the circumstances, the best model should be chosen after considering models with lags from 1 to 7 days (Jin et al. 2022).

It is important to examine the dispersion value of the Poisson distribution in order to ascertain its adherence to the underlying assumptions. The Poisson distribution assumes that the dependent variable has variance equal to the mean. In the event that the existing model does not satisfy the underlying assumptions, it is advisable to explore alternative models that offer greater precision. The present study has shown a dispersion coefficient of 6.3, signifying that the model exhibits overdispersion. Consequently, the utilisation of additional models is necessary to achieve accurate measurement and reliable estimation. The quasi-Poisson model and the negative binomial model have been widely recognised as effective approaches for addressing the dispersion parameter (Cameron & Trivedi 1998; Gabriella, Abdullah & Soemartojo 2019; Seyoum, Ndlovu & Zewotir 2016), which accounts for the discrepancy between the variance and the mean of the data. In general, it can be observed that the negative binomial model with a lag of 6 exhibits better results compared to the quasi-Poisson model. The model exhibits the highest log likelihood and the lowest values for both AIC and BIC, which indicates it as the best option. Moreover, the *p*-values derived from the deviance test provide no indication of any lack-of-fit in the model that was fitted. As shown in Figure 1, the quantile-quantile plot (Q-Q plot) demonstrates that the GLM fitted with a negative binomial distribution accurately fits with the observed distribution. The alignment of the line in the negative binomial regression corresponds to the positioning of the dots. Therefore, the negative binomial regression model with lag effect is a more suitable model for our count data. This finding is consistent with that of Jin et al. (2022), who reported that the seventh day following exposure to pollution exhibited the most significant impact on hospital admissions among individuals with respiratory system diseases.

TABLE 4. Model selection

Model	Lag 0	Lag 1	Lag 2	Lag 3	Lag 4	Lag 5	Lag 6	Lag 7
Poisson								
Log-likelihood	-6198	-6550	-6531	-6475	-6490	-6408	-6335	-6459
Degree of freedom	15	15	16	15	14	16	18	16
AIC	12427	13131	13094	12980	13007	12848	12707	12950
BIC	12500	13204	13172	13054	13076	12926	12795	13028
Deviance	6006	6710	6671	6560	6588	6425	6280	6527
p-value (Deviance test)	0	0	0	0	0	0	0	0
Number of significant variables	7	7	8	7	6	8	10	8
Quasi-Poisson								
Dispersion	6.1	6.9	6.9	6.8	6.7	6.6	6.4	6.6
QAIC	12456	13305	13277	13149	13163	13064	12906	13138
QBIC	12899	13775	13781	13545	13590	13513	13377	13622
Deviance	5884	6722	6680	6597	6598	6490	6323	6549
Number of significant variables	7	6	7	4	5	6	7	7
Negative binomial								
Log-likelihood	-4548	-4601	-4592	-4586	-4586	-4583	-4581	-4590
Degree of freedom	15	15	15	14	13	15	15	13
AIC	9125	9231	9214	9199	9198	9195	9193	9207
BIC	9199	9304	9288	9267	9261	9268	9266	9270
Deviance	1025	1019	1014	1016	1015	1018	1022	1015
p-value (Deviance test)	0.0771	0.0978	0.1169	0.1147	0.1237	0.1011	0.0861	0.1240
Number of significant variables	6	6	6	5	4	6	6	4

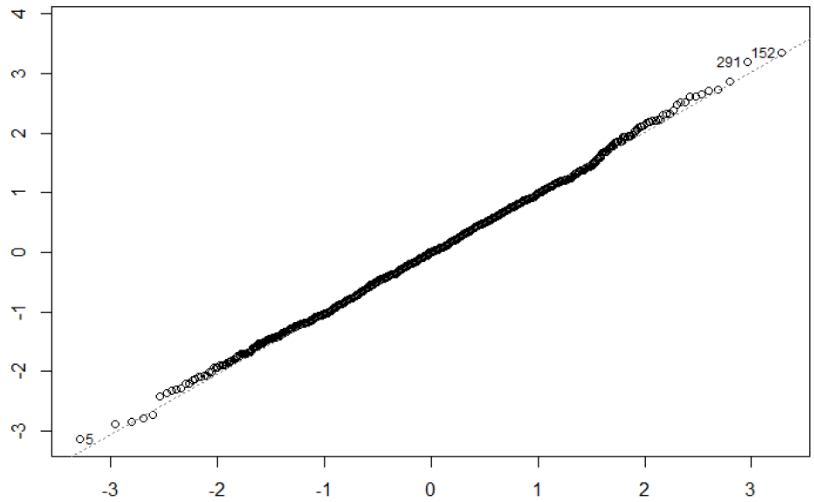

FIGURE 1. Q-Q plot for negative binomial regression model

Referring to the estimated results of the β coefficient for both models in Table 5, it was found that the PM_{10} component in both models had a positive relationship with hospitalisation for respiratory system diseases. This finding is supported by a study conducted by Atkinson et al. (1999) and Chen, Mengersen and Tong (2006) who stated that PM_{10} components have been a major contributor to hospitalisation due to respiratory system diseases such as asthma, bronchitis, pneumonia and emphysema. The results of the study clearly show that every increase in the PM_{10} component will cause the number of hospitalisations for respiratory system diseases to increase. According to DOE (2006), API readings are also determined based on the concentration of PM_{10} and $PM_{2.5}$ components which are dominant pollutants most of the time, especially during the occurrence of haze in Malaysia. $PM_{2.5}$ component has become a yardstick in the calculation of API readings starting in 2017 and it has been used in the selection of states in this study. Although the $PM_{2.5}$ component is said to be more dangerous than the PM_{10} component due to its smaller particle size, the PM_{10} component has a more significant influence in this study than the $PM_{2.5}$ component. Overall, the quasi-Poisson lag 6 model was not chosen because it did not provide the best statistical model evaluation results in this study. Therefore, the criteria of the best model have been met by the lag 6 negative binomial model based on the results of statistical model evaluation and more practically based on previous studies.

Table 6 displays the findings of a lag 6 negative binomial regression that examined the impact of pollution and weather on hospital admissions for patients with respiratory system disorders. There is a strong correlation between the number of respiratory system patients admitted to the hospital during haze and the concentrations of PM_{10}, NO_2, CO, and O_3, as well as wind speed and UV rays for selected states. If we assume that all other independent variables in the model remain constant, then we can interpret the lag 6 negative binomial regression coefficient as follows: for a one-unit change in the independent variable, we can expect the difference in the logs of expected hospital admission counts to change by the respective regression coefficient. For instance, if you raise X by 1 unit, ln μ_i will rise by β units. The expected value of μ_i expressed in units of β, rises exponentially with each unit of X. In exponential form, the approximate equation is as follows:·

$$\mu_i = e^{5.9201} \cdot e^{0.0014PM_{10,t-6}} \cdot e^{0.0225NO_{2,t-6}} \cdot e^{-0.4506CO_{t-6}} \cdot e^{-0.0049O_{3,t-6}} \cdot e^{0.1417WS_{t-6}} \cdot e^{-0.0005UV_{t-6}} e^{-2.7786PJ} \cdot e^{-1.2432KL} \cdot e^{-0.3939PK} \cdot e^{1.0248PG} \cdot e^{-1.1061MA} \cdot e^{-0.9249NS} \cdot e^{-0.8051PA} \quad (4)$$

Hospital admission incidence rate ratios per unit change in contributing factors are interpreted in Table 6 using lag 6 negative binomial regression. The exponentiated value of the regression coefficient provides

TABLE 5. Best model selection

Model	quasi-Poisson Lag 6			Negative Binomial Lag 6		
Variables		Std. Error	p-Value		Std. Error	p-Value
Constant	6.7050	0.2559	< 0.001***	5.9201	0.1025	< 0.001***
Air Pollutants						
Particulate matter (PM_{10})	0.0012	0.0007	0.076 .	0.0014	0.0007	0.054 .
Nitrogen dioxide (NO_2)	0.0251	0.0036	< 0.001***	0.0225	0.0039	< 0.001***
Carbon monoxide (CO)	-0.4639	0.0802	< 0.001***	-0.4506	0.0907	< 0.001***
Ozone (O_3)	-0.0061	0.0018	< 0.001***	-0.0049	0.0019	0.009**
Meteorology Factors						
Wind Speed (WS)	0.1409	0.0424	< 0.001***	0.1417	0.0429	< 0.001***
UV Radiation (UV)	-0.0007	0.0001	< 0.001***	-0.0005	0.0001	< 0.001***
Relative Humidity (RH)	-0.0090	0.0027	< 0.001***	-	-	-
States						
[Reference group: Selangor]						
Putrajaya (PJ)	-2.7476	0.0671	< 0.001***	-2.7786	0.0543	< 0.001***
Kuala Lumpur (KL)	-1.2745	0.0315	< 0.001***	-1.2432	0.0321	< 0.001***
Perak (PK)	-0.3609	0.0379	< 0.001***	-0.3939	0.0436	< 0.001***
Penang (PG)	-0.9997	0.0400	< 0.001***	-1.0248	0.0437	< 0.001***
Melaka (MA)	-1.0676	0.0432	< 0.001***	-1.1061	0.0472	< 0.001***
Negeri Sembilan (NS)	-0.9016	0.0372	< 0.001***	-0.9249	0.0422	< 0.001***
Pahang (PA)	-0.7466	0.0509	< 0.001***	-0.8051	0.0556	< 0.001***
AIC		12906.43			9192.74	
BIC		13377.02			9265.99	
Deviance		6322.90			1022.44	

***, **, *, and . indicate that the parameter is significant at the significance levels of 0.001, 0.01, 0.05, and 0.1, respectively.

an explanation for this. Hospitalisations due to respiratory illnesses rise by 0.14 and 2.28 percentage points for every one unit increase in the pollutant component factor PM_{10} and NO_2, respectively. Hospitalizations for respiratory illnesses were roughly one-third as common in Melaka as they were in Selangor, as measured by the IRR of 0.33. Table 6 provides a comprehensive breakdown of how each independent variable influenced μ_i.

This study identified potential contributors to the high frequency of hospitalisations for respiratory system diseases. It has been shown that PM_{10}, NO_2, CO, and O_3 components, as well as wind speed and UV ray exposure, significantly affect hospitalisation rates in some states. The analysis showed a link between the presence of PM_{10} and an increase in the number of hospitalisations for respiratory diseases. According to Unver et al. (2019), respiratory-related hospitalisations increased by 2.57 percent for every 10 g/m^3 increase in PM_{10} concentration level. Asthma attacks increased by 28.2 percent when PM_{10} levels increased by 1 g/m^3 (Raffee et al. 2018). Because these particles can enter the respiratory system and be deposited on the lung surface, they contribute to an increase in respiratory disease hospitalisations (WHO 2022). This PM_{10} component is essential to the viability of the study because it is linked to respiratory diseases like asthma, bronchitis, pneumonia, and emphysema (Atkinson et al. 1999; Chen, Mengersen & Tong 2006).

The study also found that a 2.28-percent increase in hospital admissions was associated with a one-unit increase in NO_2 concentration. Farhat et al. (2005) and Jevtic et al. (2014) found that NO_2 exposure was linked to higher rates of hospitalisation for pneumonia (17.6%) and asthma (31.4%), as well as increased emergency room visits for lower respiratory tract infections (18.4%). According to the World Health Organization (2005), even short-term exposure to NO_2 can irritate the throat and lungs, and long-term exposure can greatly increase the risk of developing asthma.

TABLE 6. Parameter estimation for negative binomial lag 6 Model and variable effects on hospital admissions

Variables	β	IRR	95% Confident Interval exp(β)		Changes on (%)
			Lower boundaries	Upper boundaries	
Constant	5.9201	372.4490	5.7187	6.1219	-
Air Pollutants					
Particulate matter (PM_{10})	0.0014	1.0014	-3.3765	0.0028	0.14
Nitrogen dioxide (NO_2)	0.0225	1.0228	1.4660	0.0303	2.28
Carbon monoxide (CO)	-0.4506	0.6372	-6.2854	-0.2726	-36.28
Ozone (O_3)	-0.0049	0.9951	-8.5640	-0.0012	-0.49
Meteorology Factors					
Wind Speed (WS)	0.1417	1.1522	5.7449	0.2261	15.22
UV Radiation (UV)	-0.0005	0.9995	-7.7278	-0.0002	-0.05
States					
[Reference group: Selangor]					
Putrajaya (PJ)	-2.7786	0.0621	-2.8856	-2.6719	-93.79
Kuala Lumpur (KL)	-1.2432	0.2885	-1.3064	-1.1800	-71.15
Perak (PK)	-0.3939	0.6744	-4.7966	-0.3083	-32.56
Penang (PG)	-1.0248	0.3587	-1.1110	-0.9387	-64.13
Melaka (MA)	-1.1061	0.3308	-1.1992	-1.0132	-66.92
Negeri Sembilan (NS)	-0.9249	0.3966	-1.0083	-0.8417	-60.34
Pahang (PA)	-0.8051	0.4470	-9.1476	-0.6957	-55.3

In addition, the CO factor has greatly contributed to the 36.28 percent decline in hospitalisation rates for patients with respiratory systems. Short-term exposure to CO was associated with a reduced risk of hospitalisation for COPD patients, which is consistent with the finding of Tian et al. (2014). According to a study conducted by Ito, Thurston and Silverman (2007), while carbon monoxide was shown to increase asthma-related emergency room visits in single-pollutant models, the risk estimate for carbon monoxide became negative when nitrogen dioxide was added to the model. These findings might indicate real variations in the health outcomes of the specific pollutants but distinguishing between such factors is challenging in multipollutant models.

Furthermore, this research demonstrated an inverse association between the O_3 component and hospitalisation for respiratory system diseases. According to the results, there will be a 0.49% decrease in the number of patients admitted to the hospital due to problems with their respiratory systems for every one unit increase in O_3 concentration. Capraz and Deniz (2021) found that patients with asthma, pneumonia, COPD, and bronchitis were more likely to be hospitalised after being exposed to O_3. However, de Souza et al. (2014) found that in Campo Grande, Brazil, O_3 had a negative effect on respiratory diseases with a lag of 2 to 4 days.

Hospitalisation rates for people who have problems with their respiratory systems are most affected by the wind speed. If the wind speed factor were to increase by one unit, for instance, respiratory system patients admitted to hospitals would increase by 15.22%. Increases in wind speed were also positively related to hospitalisation for adult asthmatics, as found by Bodaghkhani et al. (2019). In general, increased wind speed hastens the spread of pollutant components over a larger area. Because pollutant components spread quickly, those with weakened immune systems are more likely to suffer serious consequences from exposure.

UV exposure has a significant impact on hospital admissions for respiratory system patients, although a less stated impact when compared to other meteorological factors. In this study, for every one unit increase in UV factor, there was a 5% decrease in hospital admissions for respiratory patients. These findings are in line a study by Huber et al. (2012), which found that patients with COPD who spent more time outdoors had fewer hospitalisations. The ultraviolet rays of sunlight may result in the production of nitrogen monoxide, which can reduce the inflammatory response of the respiratory tract wall.

Patients with respiratory conditions who were being considered for hospital admission did not have their admission decisions influenced by $PM_{2.5}$. Unlike previous research, this study did not find that the $PM_{2.5}$ component significantly affected hospital admissions for respiratory system disorders. Temperature, humidity, wind direction, and the SO_2 component factor have no significant influence on the prevalence of respiratory-system disease hospitalisations.

Conclusion

The study showed significant correlations between the concentration of PM_{10} and the average daily number of hospitalisations for respiratory diseases, indicating short-term effects of PM_{10} on respiratory disease hospitalisation. Additional factors, such as levels of PM_{10}, NO_2, CO, and O_3, as well as wind speed and ultraviolet (UV) radiation, have been discovered to have an impact on the number of hospital admissions for respiratory diseases. Consequently, the daily admission rate of patients with respiratory diseases to hospitals during the haze period exhibits variability across the chosen states, depending upon the pollutant component and prevailing meteorological conditions. The best possible estimation of hospitalisation probability for patients with respiratory diseases resulting from exposure to pollution components is obtained through the utilisation of a model that incorporates a lag effect, accounting for the delayed onset of symptoms.

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*Corresponding author; email: nm@ukm.edu.my