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AGE-STRATIFIED IMPACT OF AIR POLLUTION ON RESPIRATORY SYSTEM HOSPITALIZATIONS USING DLNM: A HAZE EPISODE ANALYSIS

(*Impak Stratifikasi-Umur bagi Pencemaran Udara Terhadap Kemasukan Hospital Sistem Pernafasan Menggunakan DLNM: Suatu Analisis Episod Jerebu*)

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ABSTRACT

Air pollution is a major environmental risk factor for respiratory diseases, with its impact potentially varying across age groups and during different haze episodes. The haze phenomenon, characterized by elevated concentrations of ambient air pollutants exceeding 100 µg/m^3, is associated with increased respiratory health risks in exposed populations. This study aims to investigate the age stratified lagged associations between air pollutants and respiratory system hospitalizations across three defined episodes: pre-haze, haze and post-haze, using Distributed Lag Non Linear Models (DLNM). Daily counts of respiratory system hospital admissions in Peninsular Malaysia and air pollutant concentrations (PM_{10}, SO_2, NO_2, O_3 and CO) were obtained from 2000 to 2019. The data were stratified by three age groups: children (0–14 years), working adults (15–64 years) and the elderly (65+ years). DLNM was employed to estimate the delayed and non linear effects of pollutants on respiratory system hospitalizations during the pre-haze, haze and post-haze periods. The study found that the effects of air pollutants on respiratory hospital admissions varied by age group and haze episodes. The working adults group consistently showed the highest and most prolonged risks, especially during the haze period. Children exhibited immediate but shorter effects, while the elderly experienced delayed but significant impacts, particularly from SO_2 and CO during the post-haze episode. Each pollutant showed distinct lag patterns across age groups, with relative risks (RR) indicating age and haze episodes vulnerabilities. DLNM showed varying air pollution effects across age groups and haze episodes, emphasizing the need for age targeted public health strategies.

Keywords: air pollutant; age group; pre-haze; post-haze; Distributed Lag Non Linear Model (DLNM)

ABSTRAK

Pencemaran udara merupakan faktor utama risiko alam sekitar untuk penyakit sistem pernafasan, dengan kesannya berbeza mengikut kumpulan umur dan episod kualiti udara. Fenomena jerebu, dengan peningkatan mendadak kepekatan bahan pencemar di udara ambien, dipercayai berkait rapat dengan peningkatan risiko kesihatan sistem pernafasan dalam kalangan populasi yang terdedah. Kajian ini bertujuan untuk mengkaji perkaitan tertunda mengikut stratifikasi kumpulan umur antara bahan pencemar udara dengan kemasukan ke hospital akibat penyakit sistem pernafasan dalam tiga episod: pra jerebu, semasa jerebu dan pasca jerebu, menggunakan Model Lag Teragih Bukan Linear (DLNM). Data harian kemasukan hospital akibat penyakit sistem pernafasan di Semenanjung Malaysia serta kepekatan pencemar udara (PM_{10}, SO_2, NO_2, O_3 dan CO) diperoleh bagi tempoh 2000 hingga 2019. Data ini telah distratifikasi kepada tiga kumpulan umur: kanak-kanak (0–14 tahun), dewasa bekerja (15–64 tahun) dan warga emas (65 tahun ke atas). Model DLNM digunakan untuk menganggarkan kesan tertunda dan tidak linear bahan pencemar terhadap kemasukan hospital dalam ketiga-tiga episod. Hasil kajian menunjukkan bahawa semasa tempoh jerebu, kanak-kanak mengalami perkaitan yang paling kuat dan segera dengan kesemua bahan pencemar. Golongan dewasa bekerja paling terkesan oleh NO_2, manakala warga emas menunjukkan peningkatan risiko terhadap PM_{10}, NO_2, O_3 dan CO. Dalam tempoh pra jerebu, pengurangan risiko diperhatikan dalam kalangan kanak-kanak, manakala pendedahan kepada SO_2 dan CO dikaitkan dengan peningkatan kemasukan hospital dalam kalangan dewasa dan warga emas. Dalam tempoh pasca jerebu, O_3 secara konsisten menyumbang kepada peningkatan risiko untuk semua kumpulan umur, dengan kanak-kanak kekal sebagai kumpulan paling terkesan. Dapatan ini menunjukkan bahawa DLNM dapat mengenal pasti variasi kesan pencemaran udara merentas kumpulan umur dan episod jerebu, sekali gus menegaskan keperluan strategi kesihatan awam yang bersasar mengikut kumpulan umur.

Kata kunci: pencemaran udara; sistem pernafasan; stratifikasi-umur; episod jerebu; Model Lag Teragih Bukan Linear (DLNM)

1. Introduction

Air pollution is a serious environmental issue that significantly contributes to the global burden of disease, particularly in relation to respiratory illnesses. In Malaysia and other Southeast Asian countries, recurring transboundary haze incidents are mainly caused by large-scale biomass burning, frequently elevating ambient air pollution to hazardous levels ($PM_{10} >$ 250 µg/m³ or $PM_{2.5} >$ 150 µg/m³) as defined by the Malaysian Air Pollutant Index (API). During these episodes, levels of pollutants such as particulate matter (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3) and carbon monoxide (CO) can exceed national and international safety thresholds. These elevated levels are strongly associated with various adverse health outcomes, particularly respiratory diseases. Over the past five years, the Department of Statistics Malaysia has consistently reported pneumonia as the second leading cause of death in the country, accounting for 11.1% to 13.7% of total deaths annually. However, a notable shift occurred in 2021, when pneumonia dropped to the third leading cause, overtaken by COVID-19, which accounted for 19.8% of all deaths that year (Department of Statistics 2022). This trend highlights the ongoing and increasing burden of respiratory related mortality in Malaysia, exacerbated by both infectious diseases and environmental exposures such as air pollution.

Numerous epidemiological studies have confirmed the association between elevated pollutant levels and increased respiratory morbidity. For instance, Dominick *et al*. (2012) observed that elevated concentrations of PM_{10} and NO_2 were strongly associated with daily hospital admissions due to respiratory diseases. These effects are often more pronounced during haze episodes, which correspond with spikes in respiratory hospitalizations (Cheong *et al*. 2019). The health effects of air pollutants are not necessarily instantaneous but they may be delayed and vary in magnitude and duration depending on pollutant type, environmental conditions and individual susceptibility.

Age significantly influences susceptibility to air pollution. Children and the elderly are typically more vulnerable due to underdeveloped or compromised respiratory and immune systems. Aithal *et al*. (2023) noted that children's respiratory systems are still developing, making them particularly sensitive to pollutant exposure. Additionally, Andrade *et al*. (2023) concluded that poor air quality acts as a detrimental factor to the health of older adults, particularly during physical activities, leading to increased occurrences of cardiovascular and respiratory diseases. Conversely, working adults may also experience high exposure due to outdoor activities and commuting patterns but may exhibit different risk patterns due to better baseline health (Wong *et al*. 2021).While numerous studies in Malaysia have assessed the relationship between air pollution and respiratory outcomes, few have focused on differentiating health risks by age group or across distinct haze periods, which remains an important gap addressed in the present study. Moreover, many existing studies rely on linear or short term models that may not capture the delayed and non linear effects of air pollution exposure. The Distributed Lag Non Linear Model (DLNM), introduced by Gasparrini (2011), offers a methodological advancement by allowing for the estimation of both delayed (lagged) and non linear associations between environmental exposures and health outcomes. This approach has been increasingly applied in air pollution and health studies globally.

The distributed lag non-linear model (DLNM) has been widely used in epidemiology and environmental health research to characterize complex non-linear and delayed effects between environmental exposures and health outcomes. For example, DLNM have been applied to study the lagged association between fine particulate matter ($PM_{2.5}$) and intensive care unit admissions for pneumonia, revealing increases in relative risk at specific lag days following exposure (Zhang *et al*. 2017). Similarly, time-series analyses in urban settings have used DLNMs to quantify how multiple air pollutants influence outpatient visits for allergic rhinitis, highlighting cumulative effects over a 30-day lag period (Yang *et al*. 2022). In respiratory epidemiology, DLNM frameworks have been used in both China and Malaysia to examine how short-term exposure to particulate matter is related to hospital admissions, often demonstrating non-linear exposure–response curves and delayed health effects. A recent systematic review of DLNM applications emphasized the model's value in capturing exposure–lag–response relationships across a range of environmental exposures and adverse health outcomes, including morbidity and hospitalization. Despite this growing body of work, few studies have stratified lagged effects by both age and gender in the context of haze episodes in Malaysia, nor have they comprehensively modeled the 30-day lag structure of respiratory hospital admissions associated with haze exposure while adjusting for meteorological confounders. The current study therefore contributes to the literature by applying DLNM to a long-term haze dataset with a large sample of respiratory admissions and by evaluating differential susceptibility across demographic groups, offering insights that are directly relevant to public health policy and air quality management in haze-prone regions.

This study investigates the lagged and non linear associations between major air pollutants and respiratory hospital admissions across three defined periods: pre-haze, haze, and post-haze, with stratification by age group. Applying the Distributed Lag Non Linear Model (DLNM) to nationwide data from Peninsular Malaysia spanning 2000 to 2019, the analysis aims to uncover age specific and time specific vulnerabilities. The DLNM approach was selected because it extends beyond the limitations of traditional time-series or regression models used in previous studies, which often assume a linear and immediate relationship between exposure and outcome. In contrast, DLNM enables the modelling of complex, non-linear exposure–response relationships and distributed lag structures, capturing the delayed health effects of air pollution across multiple days or weeks. This makes it particularly suitable for evaluating age-specific and temporal vulnerabilities to haze exposure in Malaysia's context. The findings aim to provide critical evidence to support targeted public health strategies and improve early warning systems, particularly during haze events and other high-risk environmental periods.

2. Research Method

2.1. *Study area*

This study was conducted in Peninsular Malaysia, which comprises 11 states. The region frequently experiences transboundary haze events, especially during the Southwest monsoon season, when smoke from large scale biomass burning in neighbouring countries significantly deteriorates air quality. With its high population density, diverse socioeconomic composition and varied environmental exposures, Peninsular Malaysia provides a meaningful and representative setting for assessing the health effects of air pollution. The analysis included all hospitals in Peninsular Malaysia that report to the Ministry of Health (MOH). Air pollutant data were obtained from all fixed site air quality monitoring stations operated by the Department of Environment (DOE) across the region. As the majority of Malaysia's population resides in Peninsular Malaysia, findings from this study are considered reflective of the broader national impact of air pollution on respiratory health. Data were collected for the period between 1 January 2000 and 31 December 2019.

2.2. *Data collection*

Daily counts of hospital admissions due to respiratory system diseases (ICD-10 codes J00–J99) were obtained from the Ministry of Health (MOH), Malaysia, for government hospitals in Peninsular Malaysia. A detailed list of the hospitals involved available in the Supplementary Materials 1. The data were stratified into three age groups: children (0–14 years), working adults (15–64 years), and the elderly (65 years and above) to assess age specific vulnerability. This categorization follows the age structure commonly applied in environmental epidemiology studies (Wong *et al*. 2010; Yang *et al*. 2022), where children and the elderly are recognized as more susceptible to air pollution due to their developing or weakened respiratory and immune systems, while working adults serve as a comparative baseline group.

Environmental data including daily average concentrations of five major air pollutants: particulate matter ≤10 µm (PM_{10}), sulfur dioxide (SO_2), nitrogen dioxide (NO_2), ozone (O_3) and carbon monoxide (CO) were sourced from DOE's fixed-site air quality monitoring stations. Meteorological variables such as daily mean temperature and relative humidity were also included as potential cofounders. Malaysia has experienced recurrent haze episodes over the past several decades, primarily driven by transboundary smoke pollution from large-scale biomass burning and forest fires in the region, particularly during the Southwest Monsoon period. Major haze episodes were recorded in 1997–1998, 2005, 2013, 2015, and 2019, with several of these events resulting in hazardous air quality levels across Peninsular Malaysia and East Malaysia. Among these, the 1997–1998 and 2015 haze episodes were widely recognised as the most severe, leading to prolonged periods of elevated particulate matter concentrations and widespread public health concern. The study period was divided into three haze episodes based on seasonal trends and satellite fire hotspot data: pre-haze (March to June), haze (July to October), and post-haze (November to February). This classification was guided by previous research findings (Norela *et al*. 2013; Sulong *et al*. 2017), as well as haze alerts from the Department of Environment (DOE) and satellite fire hotspot data, which reflect the typical timing and intensity of haze episodes in Malaysia.

2.3. *Statistical methods*

2.3.1. *Data processing and imputation*

Air pollutant concentrations originally recorded in parts per million (ppm) were converted to micrograms per cubic meter ($\mu g/m^3$), denoted as variable Y. The conversion assumes a temperature of 25°C and atmospheric pressure of 1 atm, except for PM_{10} which was already recorded in $\mu g/m^3$ by monitoring stations. The conversion formula used in this study is:

$$Y = \left(\frac{(X_{ppm})(Molecular\ Weight)}{25}\right) \times 1000 \tag{1}$$

where the molecular weights are CO = 28.01 g/mol, O_3 = 48.00 g/mol, NO_2 = 46.0055 g/mol, and SO_2 = 64.07 g/mol.

The Predictive Mean Matching (PMM) method was applied for missing values in the dataset, which is one of the multiple imputation techniques under the Multiple Imputation by Chained Equations (MICE) framework. PMM is particularly effective in preserving the distribution of the original data and reducing potential biases due to missingness of the data. The proportion of missing data was relatively low, not exceeding 5% across all variables, which is generally considered acceptable for maintaining data validity in multiple imputation analysis (Peng & Chen 2018; Schafer 1999). As the missingness mechanism was Missing at Random (MAR), PMM was considered an appropriate imputation method.

2.3.2. *Model development for the association between air pollutants and respiratory diseases using DLNM*

The delayed and non linear effects of air pollutants on respiratory hospital admissions were examined using the Distributed Lag Non Linear Model (DLNM) within a quasi-Poisson regression framework. DLNM was used to estimate the lagged and non-linear effects of haze exposure on daily respiratory admissions. The model uses a cross-basis function to simultaneously represent the exposure–response and lag–response relationship. Natural cubic splines were applied for the exposure and lag dimensions, with a lag period of 0–30 days. This modeling approach is particularly suitable for time series count data that exhibit overdispersion, allowing for the assessment of both non linear exposure response relationships and lagged effects over time. Models were constructed separately for all age groups and stratified by three distinct haze periods. This stratified approach facilitated the identification of population specific vulnerabilities and seasonal variations in respiratory health risks.

(a) General Model Structure

The general time series model for this study is given by:

$$g(\mu_t) = \alpha + \sum_{j=1}^{J} s_j(x_{tj};\beta_j) + \sum_{k=1}^{K} \gamma_k \rho_k \tag{2}$$

where $\mu_t = E(Y_t)$ represents the expected daily hospital admissions, and $g(.)$ is a log link function. The function $s_j(.)$ represents a smooth function for predictor x_{tj} estimated using basis functions. J denotes the number of predictors modeled using smooth function, while K

represent the number of additional linear covariates ρ_k such as day of the week or day of the year with associated coefficients γ_k . In this study, predictors x_{tj} include daily average pollutant concentrations and meteorological variables. While air pollutant effects are assumed to be primarily linear, meteorological factors such as temperature, humidity, and wind speed are modeled using non linear functions to account for their complex effects.

(b) Modelling Non-Linear Exposure Response

The non linear relationship between exposure and outcome is modeled using basis functions. The transformation is defined as:

$$s(x_t; \beta) = z_t^T \beta \tag{3}$$

$s(x_t; \beta)$ represent the smooth function applied to the exposure variable x_t where z_t is the t-th row of the basis matrix derived from the original exposure variable. β is the parameter vector of regression coefficients estimated from the model. Hence, $z_t^T \beta$ provides the estimated log risk of respiratory hospital admission associated with specific exposure level on day t.

(c) Lag Effect Structure

The delayed effects are captured by having an additional dimension representing lag is incorporated into the model. The exposure vector :

$$z_t = (x_t, x_{t-1}, x_{t-2}, \dots, x_{t-L}) \tag{4}$$

where each element represents the pollutant concentration on day t and up to L days before. L is the maximum lag length set at 30. This approach creates a comprehensive representation of cumulative and delayed exposure, capturing both immediate and lagged associations between pollutant levels and health outcomes. The resulting vector has a dimension of $(L = 1) \times 1$, encompassing all relevant past exposure values for each time point in the dataset. By integrating this lag dimension into the model, the DLNM enables the estimation of distributed effects over time, allowing for the identification of specific time windows during which the health impact of air pollution is most pronounced.

(d) Cross Basis Function of Exposure and Lag Response

DLNM combines both exposure and lag dimensions using a bi-dimensional basis known as the cross basis function. The cross basis function allows for flexible modeling by combining two sets of basis functions: one applied to the pollutant concentration dimension and another applied to the lag dimension from 0 to 30 days. Together, these functions form a tensor product that produces a matrix of basis variables, which can then be included in the regression model as a single term. The combined cross basis function can expressed as:

$$s(x_t; \eta) = \sum_{j=1}^{v_x} \sum_{k=1}^{v_\ell} r_{tj}^{\mathrm{T}} \, . \, c_{\cdot k} \, \eta_{jk} = w_t^T . \eta \tag{5}$$

where r_{tj} is basis term for exposure dimension and c_k is basis term for the lag dimension. $w_t^T \eta$ is the cross basis matrix for day t and η is the vector of parameters to be estimated.

(e) Final model of DLNM

The final statistical model used in this study was developed to estimate the association between air pollutant exposure and daily hospital admissions for respiratory diseases across different haze episodes. A quasi-Poisson regression was employed to account for overdispersion in the count data, with the exposure–lag–response relationship for each air pollutant modeled using a cross basis function derived from DLNM. The final model applied in this study is specified as follows:

$$\log E(Y_t) = [\,\alpha + \beta X_{t,l} + ns(Time_t, df) + ns(DOY, df) + ns(Temp_t, df) + ns(Humidity_t, df) + ns(Wind_t, df) + factor(DOW_t)]. \tag{6}$$

In this model, potential multicollinearity may arise because certain explanatory variables particularly meteorological factors such as temperature, relative humidity, and wind speed. They tend to be correlated with each other and with air pollutant concentrations. In addition, temporal terms can introduce overlapping variability. Multicollinearity can inflate the standard errors of the estimated coefficients and obscure the independent effects of individual predictors. To minimize this issue, variance inflation factors (VIFs) were examined, and the degrees of freedom for spline terms were carefully selected to avoid overfitting. Furthermore, each pollutant was modeled separately in single pollutant models to reduce collinearity between pollutants. In this model, Y_t represent the daily count of hospital admissions due to respiratory diseases on calendar day t, while α is the intercept. The term $X_{t,l}$ denotes the cross basis matrix for the pollutant concentration and lag days. Natural cubic spline function denoted as $\text{ns}(.)$, were used to adjust for non linear confounding effects. Natural cubic splines with 7 df per year for time and 3 df for each meteorological variable were used, with knots placed at equally spaced percentiles of the variable distributions. This ensures smooth, flexible adjustment for long term and meteorological confounding. Specifically, $Time_t$ controls for long term trends and seasonality in the hospital admissions, while DOY (day of the year) accounts for cyclical seasonal patterns. Daily meteorological factors such as temperature,relative humidity and wind speed were included using spline terms. Relative risks (RR) with 95% confidence intervals (CI) were estimated for each exposure−lag combination. A p-value < 0.05 was considered statistically significant.

2.3.2. *Model fitting and degree of freedom selection*

The selection of degrees of freedom (df) in Eq. (6) for spline functions was guided by the Quasi-Akaike Information Criterion (QAIC), calculated as:

$$QAIC = -2L(\hat{\theta}) + 2\hat{\emptyset}k \tag{7}$$

where $L(\hat{\theta})$ is the log likehood of the fitted model, $\hat{\emptyset}$ is the estimated dispersion parameter and k is the number of parameters. Based on the lowest QAIC values, 7 degree of freedom were selected for time, day of year (DOY) and relative humidity. Detailed QAIC results for the tested df values are provided in Supplementary Material 2. Model fit was assessed using the QAIC which accounts for overdispersion. Sensitivity analyses were conducted by varying degrees of freedom for splines and lag structures. All analyses were performed using R version 2.5.1 with the "dlnm", "MICE", "spline", and "mgcv" packages.

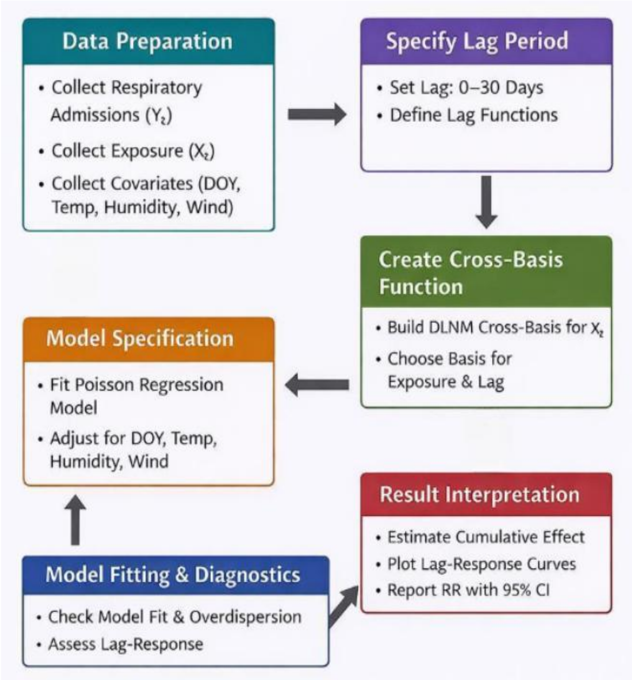


Figure 1: DLNM algorithm for respiratory admissions

3. Results and Discussions

Figure 1 presents the total number of hospital admissions for respiratory diseases by age group from 2000 to 2019. Children (ages 0–14) consistently recorded the highest number of admissions, followed by the working-age adults (15–64), while the elderly (65+) had the lowest. An increasing trend was observed across all age groups, with a particularly sharp rise in child admissions starting in 2015. By 2018, children accounted for 54.26% of total respiratory admissions, compared to 29% for working-age adults and 16.74% for the elderly. The difference in admission proportions between children and the working age group was 25.26%, while the gap between children and the elderly was 37.51%. These indicate that children were the most affected by respiratory diseases, particularly in the later years of the study.

Table 1 presents hospital admissions by gender and age group across the pre-haze, haze, and post-haze periods. Across all periods, children consistently accounted for the highest proportion of admissions, with males representing a larger share than females. During the haze period, male children constituted approximately 57.4% of total child admissions (535,962 of 933,357), while female children accounted for 42.6%. A similar male predominance was observed in the pre-haze (57.5% male vs. 42.5% female) and post-haze periods (57.5% male vs. 42.5% female). Among the working-age population, admissions were more evenly distributed by gender. During the haze episode, males accounted for 51.1% of admissions, compared to 48.9% for females. This balanced pattern was consistent across pre-haze and post-haze periods, indicating less pronounced gender disparity compared to children. In the elderly group, males consistently represented a slightly higher proportion of admissions. During the haze period, elderly males comprised 56.9% of admissions, while females accounted for 43.1%, a pattern that remained stable across all study periods. Notably, children's total admissions declined in the post-haze period, whereas the proportion of admissions among working-age adults and the elderly increased, suggesting possible delayed or cumulative effects of haze exposure in older populations. Overall, these findings highlight that children the most vulnerable group to haze-related respiratory admissions, while age and gender-specific differences indicate varying susceptibility to air pollution across demographic groups.

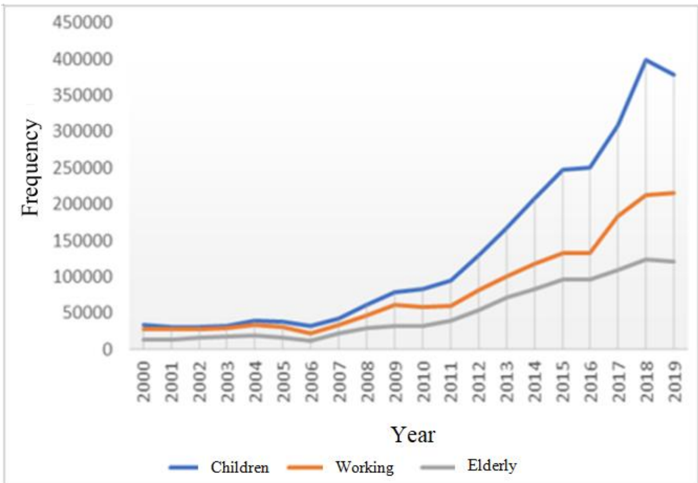
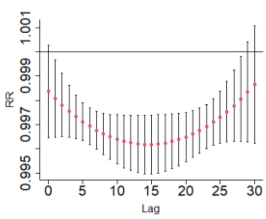
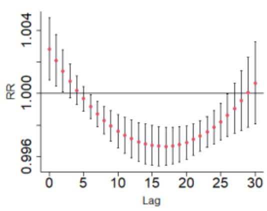
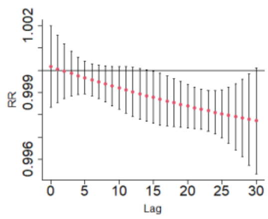
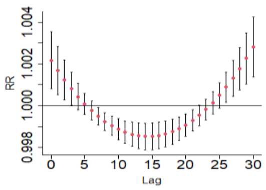
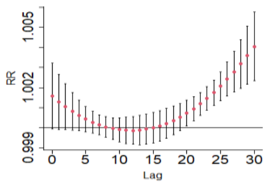
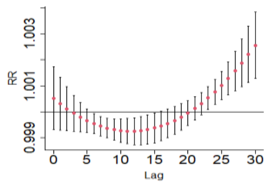


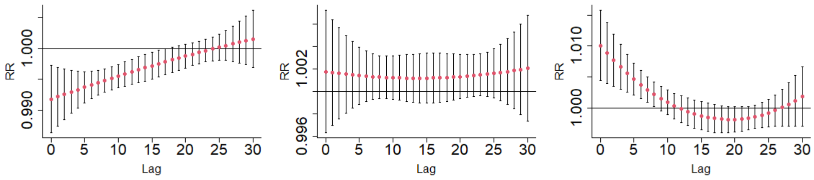
Figure 2: Total number of respiratory disease patients by year

Table 1: Hospital admissions for respiratory system diseases by age group

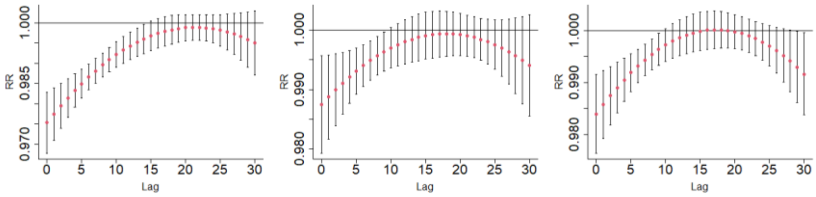
	Children		Working age		Elderly	
Gender	**Male**	**Female**	**Male**	**Female**	**Male**	**Female**
Pre-haze	511199	377162	276783	262039	189591	146554
Haze	535962	397395	274698	263350	184536	139849
Post-haze	494800	366108	280149	273751	197188	155133

Pollutants	**Episodes**	**Age Group**		
		Children	**Working Age**	**Elderly**
PM_{10}	Pre-haze			
	Haze			

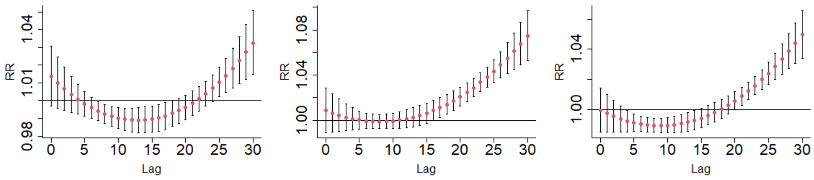
Post-haze



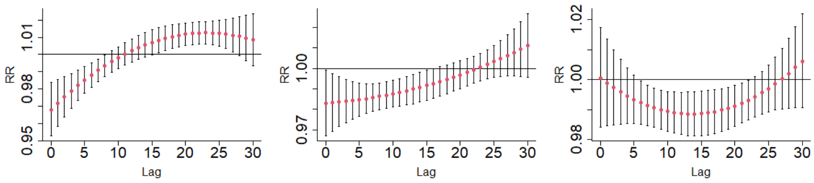
NO_2 Pre-haze



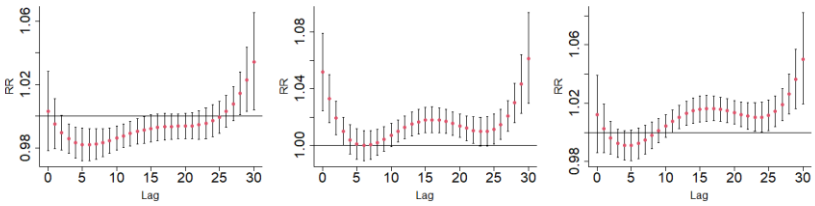
Haze



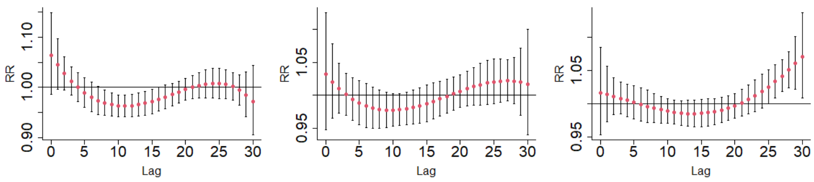
Post-haze



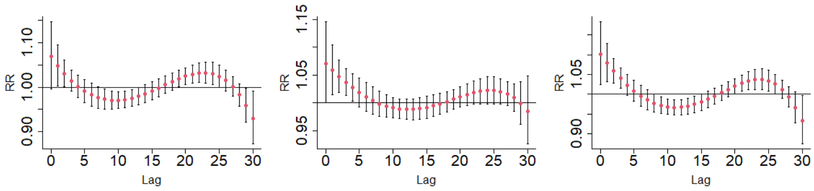
SO_2 Pre-haze



Haze



Post-haze



O_3 Pre-haze

Haze

Post-haze

CO Pre-haze

Haze

Post-haze

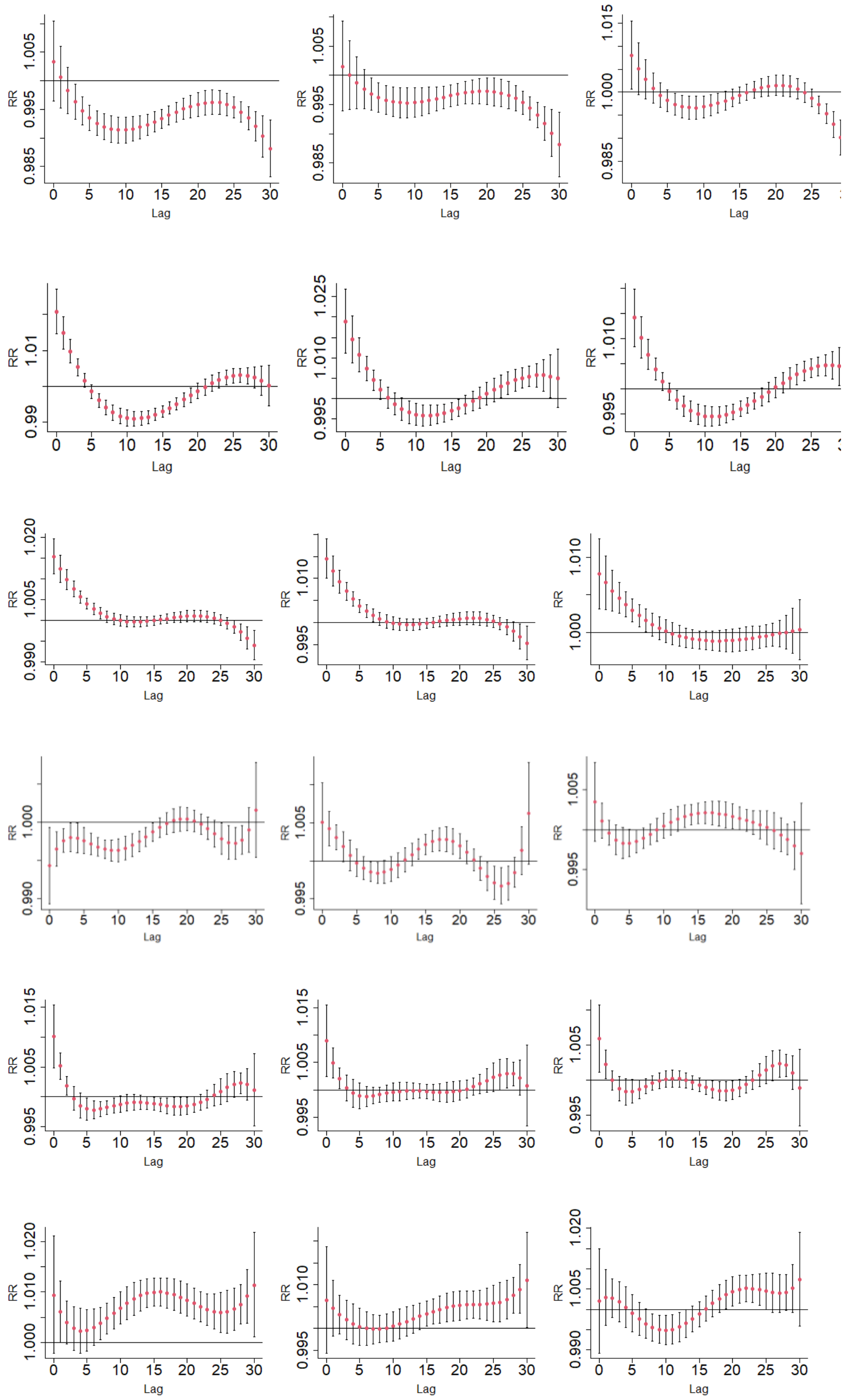


Figure 3: Relative Risk (RR) of hospital admissions by age group across each season

Figure 3 presents the relative risk (RR) of hospital admissions stratified by age group across different seasons. This allows for comparison of seasonal variations in hospitalization risk among children, adults, and older populations, highlighting which groups are more vulnerable during specific periods. According to Figure 3, during pre-haze period, a 10 μg/m³ increase in PM_{10} concentration was associated with a reduction in hospital admissions. This inverse relationship contrasts with the majority of previous studies, which typically report increased admissions with higher PM_{10} levels. Among children, there was a consistent and significant decline in respiratory hospital admissions, indicating a protective or delayed-response trend before the haze began. The observed significant decline in respiratory hospital admissions following short-term increases in PM_{10} may reflect a temporal effect harvesting effect where susceptible individuals are affected earlier. The patients had been admitted or deceased during the haze peak. This results in a temporary reduction in subsequent admissions during the early or pre-haze days. The working age group initially showed a positive significant effect at lag 0 with relative risk (RR) of 1.003 (CI:1.0009,1.0048) and lag 1 RR 1.0021 (CI:1.0005,1.0037), suggesting a short term increase in admissions. However, this was followed by a statistically significant reduction in hospitalizations between lag 7 and lag 25, possibly indicating adaptation or lagged improvements in air quality. For the elderly, no significant increase was observed during early lags, but a notable significant decrease occurred from lag 16 to lag 29, showing a delayed reduction in hospital admissions in the pre-haze stage. During the haze period, PM_{10} exposure resulted in positive and significant increases in hospital admissions, especially among the younger population. Children experienced an immediate increase starting from lag 0 with RR 1.0022 (CI:1.0008,1.0035) to lag 3, and again at lag 26 to lag 29, indicating both acute and delayed effects. For the working-age group, the elevated risk persisted and intensified from lag 20 to lag 30. The elderly did not exhibit early significant responses, but showed a delayed positive effect from lag 23 to lag 30, with a peak RR of 1.0025 (CI:1.0013,1.0038) at lag 30, indicating they may suffer longer term consequences following exposure to haze. In the post-haze episode, the effect of PM_{10} appeared to be less consistent across age groups. Children and working age group displayed no positive significant effects throughout all lag days, although a mild upward trend was noted. In contrast, the elderly demonstrated a strong immediate response, with significantly increased hospital admissions from lag 0 to lag 7, peaking at RR 1.0101 (CI:1.0045,1.0157) at lag 0, but with no significant effects observed after lag 5.Similar findings were reported by Liu *et al*. (2022), Sofwan *et al*. (2021), Phosri *et al*. (2019), and Phung *et al*. (2016), who also demonstrated a significant association between PM_{10} exposure and respiratory health outcomes, with effects varying across different lag days. This pattern suggests that elderly individuals remain sensitive to residual or lingering effects of PM_{10} even after the haze event has passed, possibly due to cumulative respiratory burden. This suggests that elderly patients are particularly vulnerable in the aftermath of haze events, likely due to residual respiratory sensitivity or pre-existing health conditions exacerbated by prior exposure of PM_{10}. Children and working adults are more sensitive during the haze period, whereas the elderly exhibit delayed or post exposure effects.

During the pre-haze period, exposure to increased NO_2 levels showed no significant positive association with hospital admissions for respiratory diseases across all age groups. In fact, the early lag days demonstrated a negative significant effect, particularly noticeable before lag 10, while no significant associations were found during later lag days (lag 10 and above) depending on the age group. The early negative association may reflect short-term behavioural adaptations and temporal effects, where individuals, especially children and the elderly, reduce outdoor exposure or seek early treatment during mild pollution episodes, leading to a temporary decline in subsequent hospital admissions. Such temporal displacement or behavioural response patterns have been observed in previous air pollution time-series and DLNM studies (Gasparrini *et al*. 2011; Samoli *et al*. 2011). In the haze period, a clear pattern of positive and delayed effects emerged. Delayed effects became more pronounced, especially among the working age group, where a significant positive association was observed from lag 16 to lag 30. Children and elderly groups also experienced positive associations, but these appeared slightly later, children at lag 25 to 30, and elderly at lag 21 to 30. Among all groups, the working age group was the most affected, both in terms of magnitude and duration of risk. Liu *et al*. (2016) reported that haze components such as NO_2 can trigger inflammation and oxidative damage, exacerbating respiratory conditions and leading to higher hospital admission rates. These findings are consistent with those of Ab Manan *et al*. (2018), Sun *et al*. (2017), and Mills *et al*. (2016), who found that an increase of 10 $\mu g/m^3$ in NO_2 concentration was associated with approximately a 1.0% increase in hospital admissions due to respiratory diseases. In the post-haze period, a delayed positive association was observed among children, particularly between lag days 16 and 27, indicating increased vulnerability in this group. However, no significant positive associations were observed among the working-age and elderly groups. Instead, a consistent reduction in hospital admissions was noted across these age groups, suggesting a possible rebound or recovery phase following the acute haze exposure.

In the pre-haze period, exposure to SO_2 had diverse lagged effects across age groups. Among children, a significant increase in hospital admissions was only observed at the later lag days (lag 28 to 30), with a peak RR of 1.0342 (CI:1.0040,1.0653), indicating a delayed health impact. The working age group displayed sporadic significant effects, particularly from lag 0 to 3, lag 11 to 21, and lag 26 to 30, suggesting both short term and prolonged lag effects. For the elderly, significant increases were evident between lag 12 to 22 and again from lag 25 to 30, showing that delayed exposure had a more pronounced impact on older individuals. During the haze episode, SO_2 exposure showed elevated risks at early lag days among children however, these associations were not statistically significant. Similarly, the working age group did not show any statistically significant association during this period. The elderly only exhibited significant increases at late lag days, from lag 26 to 30, indicating the delayed effect of SO_2 exposure during the haze. In the post-haze period, all three age groups showed clear impacts. Children showed positive significant effects at lag 1 to 2 and lag 20 to 24 pointing to both early and late responses. The working age group was significantly affected at lag 0 to 3. Among the elderly, the effects were most severe, with the highest RR observed at lag 0 1.1005 (CI:1.0239,1.1829) and further significant associations at lag 1 to 3 and lag 21 to 26. These results suggest that after haze events, SO_2 exposure continued to contribute to respiratory admissions, especially among older individuals.

The effects of increased O_3 exposure on hospital admissions showed clear variation across haze episodes and age groups. During the pre-haze period, there were no significant associations observed in any age group, except for the elderly, who showed a slight immediate effect at lag 0 RR 1.0080 (CI: 1.0006,1.0154). In the haze period, children and working age individuals were more affected, with both groups experiencing significant immediate impacts from lag 0 to lag 4. Additionally, the working age group showed delayed positive effects at lag 23 to lag 28, while the elderly were significantly affected at early lags (lag 0 to 3) and again at late lags (lag 24 to30), indicating both immediate and delayed vulnerability. In the post-haze period, the children group experienced the highest relative risk at lag 0 RR 1.0154 (CI:1.0112,1.0196) with significant effects extending to lag 6 and the working age group and elderly showed a similar short term pattern. The most vulnerable group to O_3 exposure during haze and post-haze periods appears to be children, due to their consistent and early response, while the elderly show a more episodic pattern with effects occurring mainly during the haze. The working age group is moderately affected but shows signs of both short term and delayed impacts.

The influence of increased CO levels on respiratory hospital admissions varied notably across the pre-haze, haze and post-haze periods, as well as by age group. During the pre-haze period, children showed no significant association with CO exposure. However, working age individuals demonstrated positive significant associations at lag 1 to lag 2 and again at lag 15 to lag 20, while the elderly group showed significant associations from lag 13 to lag 19 which indicating delayed effects. During the haze episode, all age groups exhibited early positive effects. Children and working age groups had significant increases in hospital admissions at lag 0–1, with working age individuals also affected at lag 27 and 28. The elderly also showed significant associations at lag 0 and again during late lag days (lag 27 and 28), highlighting a dual phase vulnerability. In the post-haze period, the impact of CO was more prolonged. Children experienced consistent and significant increases in hospital admissions from lag 7 to lag 30, while the working age group showed similar effects from lag 15 to lag 30. The elderly group also exhibited strong and significant associations during lag 20 to lag 24, suggesting that delayed effects of CO exposure were more prominent after the haze subsided. Studies have shown that elevated ambient CO levels increase hospital admissions for various respiratory conditions, including asthma, COPD, and respiratory tract infections (Song *et al*. 2023). According to Song *et al*. (2023) for every 1 mg/m^3 increase in CO concentration, hospital admissions for overall respiratory diseases increase by 13.56%. Post-haze period saw the strongest and most sustained impact of CO exposure across all age groups, especially among children and the elderly, pointing to increased vulnerability during recovery periods and the importance of extended public health monitoring after haze events.

The study found that air pollutants such as PM_{10}, NO_2, SO_2, O_3 and CO have varying impacts on respiratory admissions across different age groups. Children were mainly affected during early lag days, particularly by PM_{10}, O_3, and CO, showing immediate but short term effects. According to studies by Aithal *et al*. (2023), Chong-Neto and Filho (2025), Roche *et al*. (2024) and Wu *et al*. (2022), children are highly susceptible to the adverse effects of air pollution due to their physiological and behavioral characteristics. Their lungs and immune systems are still developing, which increases sensitivity to pollutants. Moreover, children tend to breathe through their mouths more often than adults, bypassing the natural filtration of the nasal passages, allowing more pollutants to reach the lower respiratory tract. They also inhale more air per unit of body weight, resulting in relatively higher exposure to airborne toxins such as $PM_{2.5}$, NO_2, and ozone. Additionally, children often spend more time engaged in outdoor activities, which increases their exposure to ambient pollution, especially in urban and traffic heavy areas. Working adults showed the strongest and most consistent associations, with significant relative risks observed both immediately and across longer lag periods, especially for PM_{10} and NO_2 during haze events. According to Alyami *et al*. (2025) Zheng *et al*. (2022), individuals in the working age group are generally more exposed to air pollutants due to spending more time outdoors or commuting. This increases their exposure to vehicle emissions and industrial pollutants, which over time can significantly impair lung function and raise the risk of respiratory diseases. Furthermore, working age individuals tend to inhale more air compared to the elderly due to their larger lung capacity, as noted by Ramos *et al*. (2015). Air pollution has also become a serious public health issue, and younger generations within this age group may begin to experience adverse health effects earlier than expected. The elderly, while showing fewer immediate effects, were more vulnerable to the delayed and cumulative impacts of pollutants like SO_2 and CO, particularly during post-haze periods. According to He and Borlak (2023) and Dominici *et al*. (2006), the elderly represent a vulnerable group to respiratory illnesses due to their weakened immune systems. As people age, their capacity to generate new immune cells diminishes, which reduces their ability to fight infections. This compromised immune response makes them more susceptible to serious respiratory complications, especially when exposed to air pollutants. These findings suggest that while all age groups are impacted by air pollution, working adults are most consistently affected, and the elderly are the most vulnerable to long term exposure

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4. Conclusion

This study demonstrates that the health effects of air pollutants vary significantly by age group and haze episode. The use of Distributed Lag Non Linear Models (DLNM) allowed for detailed exploration of these lagged and non-linear relationships over a 20-year period in Peninsular Malaysia. Among the three age groups, the working-age population (15–64 years) consistently showed the highest and most prolonged risks, especially during the haze episode. This group was significantly affected by PM_{10} and NO_2, with effects persisting across early and late lag days. with effects persisting across early and late lag days. The elderly (65+ years) experienced delayed but pronounced effects, especially in the post-haze period. SO_2 and CO were particularly impact for this group, reflecting their increased susceptibility to residual pollutant exposure. Children were also affected by PM_{10} and O_3, especially during the haze and post-haze periods, but the duration of significant effects was relatively shorter. CO exposure was found to have a prolonged impact across all episodes, especially in the post-haze period, affecting all age groups. Notably, elderly individuals were more sensitive to the long term effects of CO and SO_2, likely due to preexisting health vulnerabilities. While children exhibited early responses to certain pollutants, they were generally less affected over extended lag periods compared to the other groups. This study concludes that different pollutants have distinct temporal effects depending on the age group and the haze episode. The working age group is generally the most consistently affected, while the elderly are the most vulnerable to prolonged pollutant exposure. These findings highlight the need for age specific public health strategies and air quality interventions, particularly during and after haze events, to reduce the burden of respiratory diseases among susceptible populations.

The variation in lag structures across pollutants and age groups highlights the importance of age-specific risk assessments. Immediate health effects dominate for children and working-age adults during haze episodes, whereas the elderly require extended post-exposure monitoring due to their cumulative vulnerability.

Policy recommendations arising from this study include:

- Implementing real-time air quality alerts tailored by age group
- Enhancing public health messaging during and after haze events, especially for caregivers of children and elderly individuals.
- Strengthening hospital preparedness for haze-related respiratory cases with a focus on early intervention and long-term monitoring.
- Encouraging protective behavior and reducing outdoor exposure among sensitive groups, particularly during forecasted haze events.

These findings reinforce the need for multi-layered public health strategies that are sensitive to age-specific vulnerabilities. Such approaches can mitigate the short and long term health burdens associated with episodic and chronic air pollution.

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