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Comparing Stochastic Models for Forecasting Mortality in Malaysia: Lee-Carter, Booth-Maindonald-Smith, and Age-Period-Cohort

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ABSTRACT

The Human Life Table Database (HLD) provided the death rate data utilised in this study. With an emphasis on gender disparities and applying data from 2001 to 2020, this study analyses the problem of selecting the most accurate stochastic model for forecasting mortality rates in Malaysia. This study compares the Lee-Carter, Booth-Maindonald-Smith, and Age-Period-Cohort models to determine which stochastic model is more effective in predicting gender-specific death rates in Malaysia between 2021 and 2026. HLD included mortality rates for male and female participants aged 0 to 80. The data were divided into 5-year age intervals from 2001 to 2020. The Lee-Carter model, the Booth-Maindonald-Smith model, and the Age-Period-Cohort variant of the Lee-Carter model are the three stochastic models that the study applies to this dataset. The residuals and error data were analysed to determine how well each model predicted mortality rates. The model producing the lowest error values was determined to be the most suited model for forecasting mortality trends. Comparisons were conducted across the models to assess the accuracy and robustness of the models in representing the mortality dynamics for both genders in Malaysia. The Lee-Carter model was identified as the most accurate stochastic model for forecasting mortality rates in Malaysia from 2001 to 2020, as it produced the lowest error values compared to the other models.

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1. INTRODUCTION

Over the past few years, mortality rate forecasting has gained significant attention from researchers in Malaysia. This is due to the increase in human life expectancy, indicating significant advancements in healthcare and changes in lifestyle among the Malaysian population (Ibrahim et al., 2021). Insurance companies rely heavily on mortality forecasts to determine the pricing of life insurance policies, annuities, and other financial products.

Having precise projections of mortality rates allows insurers to set appropriate prices for their products, ensuring financial stability and profitability while fulfilling their responsibilities to policyholders. According to Janssen (2018), the analysis of mortality forecasting is crucial as it provides a benchmark for projecting the rate of population ageing and determining whether pension schemes are profitable. If a stochastic model cannot accurately represent mortality trends, it can lead to either underestimating or overestimating the mortality risk in a population. This can result in insufficient allocation of resources in healthcare planning or inaccurate pricing of life insurance premiums and reserves.

Therefore, accurate mortality forecasting is essential to help policymakers deal with uncertainty in estimating future deaths, which is necessary for social and population planning, particularly in countries experiencing demographic shifts, such as Malaysia (Ibrahim et al., 2021).

2. LITERATURE REVIEW

This literature review explores mortality rates, focusing on global trends and narrowing them down to the Malaysian population. It covers the suitability of the Lee-Carter model and its extensions, time series analysis, goodness-of-fit assessments, and model selection for forecasting. This analysis provides insights into mortality rate trends and the best stochastic models for accurate predictions.

2.1 Mortality Rate Data

Mortality data track rates for specific age groups over time, providing critical insights into various mortality aspects (Redzwan et al., 2023; Zulkifle et al., 2019). The Human Life Table Database (HLD) and the Department of Information Malaysia offer detailed death rates and life expectancy data categorized by gender and age (Ibrahim et al., 2021). Understanding this data requires analyzing demographic patterns and their impacts. Accurate mortality forecasting is essential for risk evaluation, life insurance pricing, and retirement fund planning. It supports population planning and social welfare policies, helping to address health challenges and prioritize public health interventions (Kamaruddin & Ismail, 2018).

While mortality trends vary across regions, significant global shifts have occurred in recent decades. Global mortality rates have shifted due to socioeconomic, epidemiological, and demographic factors. Developing countries saw substantial declines in mortality rates in the late 20th century, mirroring earlier trends in developed countries (Shair et al., 2019). The World Health Organization (WHO) reports the highest life expectancy in Europe and the Western Pacific at 78 years, followed by the Americas at 77 years. Life expectancy in the United States increased from 47 to 75 years between 1900 and 1988 (Lee et al., 1992). Similar trends are observed in Ghana and Mauritius, where life expectancy has risen significantly (Gyamerah et al., 2023; Dhandevi & Kang, 2020). Portugal has also seen notable increases, driven by reduced infant and elderly mortality rates (Bravo et al., 2010).

Amidst these global trends, Malaysia presents an interesting case study with its unique patterns of mortality rate changes. Malaysia has seen significant improvements in healthcare and living conditions, leading to increased life expectancy across all age groups and genders. Mortality rates have notably declined, particularly in infant deaths, following a J-shaped curve from birth to age 75 (Ibrahim et al., 2021). Gender differences exist, with fewer female deaths from accidents. This trend aids insurance companies in

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pricing their products accurately (Kamaruddin & Ismail, 2018). Research highlights significant increases in neonatal life expectancy from 2000 to 2018 due to medical advancements (Zulkifle et al., 2019). Post-independence, healthcare improvement has reduced mortality rates, especially in rural areas (Chang et al., 1987). Continuing this positive trajectory, recent data show a slight decline in mortality, with 48,250 deaths reported in the fourth quarter of 2023, a 4.2% decrease from 2022.

2.2 Forecasting Methods Using Stochastic Models

Stochastic mortality models, commonly used in developed economies, help price financial products and assess mortality risk (Gyamerah et al., 2023). Various techniques have been developed, like random walk models and age-specific exponential decline (Lee et al., 1992). Understanding these models is crucial for accurate mortality forecasting, benefiting healthcare and social welfare decisions. Among these models, the Lee-Carter (LC) model stands out as a particularly influential approach.

The LC model, developed by Ronald D. Lee and Lawrence Carter in 1992, is widely used for long-term mortality forecasting. It employs a log-bilinear approach, factoring in time and age to model age-specific mortality rates. The model uses Singular Value Decomposition (SVD) to create a time-varying mortality index, which is forecasted using time-series methods like ARIMA. It is praised for its simplicity, effectiveness, and ability to explain linear trends in mortality data. The LC model's flexibility and accuracy have made it popular in forecasting mortality and setting insurance premiums. However, it has limitations, including assumptions of homoscedastic errors and reliance on historical data trends, which may not account for future changes or variability in mortality rates. Despite these limitations, the LC model has served as a foundation for further developments in the field.

Building upon the original LC framework, researchers have introduced several refinements and extensions to address its shortcomings and enhance its predictive power. The LC model, a vital tool in mortality forecasting, has been refined for improved accuracy. Extensions include integrating cohort effects and applying time-series methods to capture age-specific mortality trends (Janssen, 2018) better. New techniques address variability in datasets with low death counts, such as smoothing parameters with penalized splines (Richards & Currie, 2009). These advancements enhance the model's reliability for long-term mortality projections (Ibrahim et al., 2021). While these modifications have improved the LC model, other researchers have developed alternative approaches to address specific challenges in mortality forecasting.

One such alternative is the Booth-Maindonald-Smith (BMS) model, which specifically targets the linearity assumption in the LC model. The BMS model refines the LC model by addressing its linearity assumption in the first principal component. Developed to improve mortality forecasting accuracy, the BMS model adjusts the LC approach by using the Poisson distribution to fit age-specific mortality data and applying deviance statistics to select the best-fitting period. This method corrects for deviations from linearity and produces more accurate results for Australian mortality rates than the LC model. The BMS model offers improved forecasting precision by focusing on the age distribution of deaths and incorporating these statistical adjustments (Booth et al., 2005).

While the BMS model addresses the linearity issue, another approach, the Age-Period-Cohort (APC) model, takes a different tack by incorporating cohort effects into the forecasting framework. The APC model enhances the LC model by incorporating cohort effects, which account for mortality variations across different birth years. Unlike the LC model, the APC model addresses these variations by adding cohort-specific factors and applying constraints to manage identifiability issues. This approach uses restricted cubic splines within a Generalized Linear Model (GLM) framework to estimate age, period, and cohort effects accurately. The APC model provides a more comprehensive understanding of mortality patterns and improves forecast reliability by addressing systematic changes across cohorts (Rutherford et al., 2010; Hunt & Villegas, 2015).

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2.3 Comparison between Stochastic Models on Forecasting Mortality Rates

Researchers have conducted comparative studies across different populations and scenarios to better understand the strengths and limitations of various stochastic models. In a study by Renshaw and Haberman, the APC model was compared with age-period and age-cohort models (Renshaw & Haberman, 2006). They found that the age-period model missed some cohort effects, while the age-cohort model did not fully address period effects. The APC model, which considers age, period, and cohort together, showed fewer “ripple effects” in its residual plots, indicating a better fit for the data.

Building upon this comparative approach, Cesare and Murphy (2009) compared the BMS version of the LC model, the APC model, and a Bayesian approach for forecasting mortality. They found that while LC and BMS work well for linear trends, the APC model is better for cohort-specific causes, like lung cancer. The Bayesian approach did not significantly improve upon other methods.

While these studies provided valuable insights, assessing the model’s performance in diverse geographical contexts was important. Further research by Zakiyatussariroh et al., (2014) evaluated the forecasting performance of LC and its variants using Malaysian mortality data. In-sample tests favored BMS, but out-of-sample results showed discrepancies. The LC model performed better for males, while the LM method was better for females. Using actual rates improved all models, and the researchers noted that future studies will explore these methods with different data spans.

2.4 Descriptive and Regression Analysis

While stochastic models provide powerful tools for mortality forecasting, understanding the underlying data through descriptive and regression analysis is crucial for effective model selection and interpretation. Descriptive analysis provides insights into data trends using mean, maximum, and standard deviation measures, enhancing accuracy and decision-making. It employs graphical methods and statistical models to identify and analyze patterns in data (Feyisa & Yitayaw, 2022; Hasan et al., 2022; Husin et al., 2020).

Regression analysis offers a more sophisticated approach to understanding relationships between variables, building upon these descriptive techniques. However, it comes with its own set of challenges. In regression analysis, multicollinearity occurs when explanatory variables are highly correlated, which can distort results. To detect it, researchers should check if the R-squared value is high with many insignificant variables, calculate correlation coefficients, and use auxiliary regression (Ningsih et al., 2022). Statistically, statisticians often employ the Variance Inflation Factor (VIF) to quantify the severity of multicollinearity. This measure helps identify multicollinearity by measuring how much the variance of the regression coefficients is inflated due to collinearity. A VIF value over 10 suggests multicollinearity and potential issues with model reliability (Wasim, 2023).

3. METHODOLOGY

3.1 Data

The annual data used in this study were collected from the HLD, a comprehensive repository of secondary data that includes mortality information for male and female participants aged 0 to 80 from 2001 to 2020. These secondary data were selected due to their extensive coverage and reliability, providing a robust foundation for analyzing and forecasting mortality rates across different age groups and genders in Malaysia.

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3.2 Regression Analysis

This study applies regression analysis to evaluate and compare the effectiveness of stochastic models in forecasting mortality rates. Regression tools assess model performance and accuracy in forecasting future mortality trends for both genders in Malaysia by analyzing the relationship between predictor variables and mortality outcomes. As part of the regression analysis, the study conducted a multicollinearity test to ensure the model's reliability.

3.3 Multicollinearity Test

Multicollinearity occurs when the independent variables are closely related to each other and the dependent variable in a multiple linear regression. The VIF test is a method that can describe how much uncertainty in the estimated relationship between variables increases when those variables are related (Shrestha, 2020). When VIF equals 1, the variables are not correlated. A VIF between 1 and 5 indicates a moderate correlation, while a VIF between 5 and 10 suggests a high correlation. Values exceeding 10 signal severe multicollinearity, weakening the reliability of regression coefficients (Shrestha, 2020). The formula for the VIF is calculated as:

$$VIF_i = \frac{1}{1 - R^2} = \frac{1}{Tolerance} \tag{1}$$

3.4 Stochastic Models

This study forecasts future mortality rates using various stochastic mortality models. The study aims to examine and compare the effectiveness of the LC, BMS, and APC models in predicting mortality trends for both genders in Malaysia, ensuring accurate and reliable projections.

3.5 Lee-Carter Model

According to Lee et al. (1992) in the LC Model, the log central mortality rate at age x in year t is expressed as follows:

$$ln(m_{x,t}) = a_x + b_x k_t + \varepsilon_{x,t} \tag{2}$$

Where:
$m_{x,t}$ represents the age x central mortality rate at time t,
a_x represents the typical log mortality at age x,
b_x represents how age x reacts to changes in k_t,
k_t represents the total mortality rate at time t,
$\varepsilon_{x,t}$ represents the error term at time t.

3.6 Lee Carter Extension Models

3.6.1 Booth-Maindonald-Smith Model

The BMS model improved upon the LC model by incorporating more interaction terms and using multiple terms from the singular value decomposition, as the LC model's assumptions of constant a_x and b_x terms and linear k_x were challenged (Hu, 2014). By using more interaction terms, which are the $b_x^{(i)}$ and $k_x^{(i)}$, the BMS model aims to improve the fit to the data and account for previously unexplained effects under the LC model (Hu, 2014). The formula for the BMS Model is:

https://doi.org/10.24191/mij.v6i1.3509

$$ln(m_{x,t}) = a_x + \sum_{i=t}^{n} b_x^{(i)} k_x^{(i)} + \varepsilon_{x,t} \tag{3}$$

Where:
$m_{x,t}$ represents the age x central mortality rate at time t,
a_x represents the typical log mortality at age x,
$b_x^{(i)}$ represents how age x reacts to changes in k_t,
$k_x^{(i)}$ represents the *i-th* mortality index at time t,
$\varepsilon_{x,t}$ represents the error term at time t,
n represents the rank of approximation.

3.6.2 Age Period Cohort Lee-Carter Model

According to Macdonald et al. (2007), the APC Model, which include), the variables x (age), t (period), and c (cohort), takes on a bilinear structure. Rutherford et al., (2010) stated that the method uses restricted cubic (natural) splines for the age, period, and cohort terms within a GLM framework. This approach employs a Poisson error structure, a log link function, and includes an offset of the log as follows:

$$ln(m_{x,t,c}) = a(x) + b_1(x)k_t + b_2(x)I(c) + \varepsilon_{x,t,c} \tag{4}$$

Where:
$m_{x,t,c}$ represents the force of mortality at age x in year *t* for generation c,
$a(x)$ represents the typical log mortality at age x,
$b_1(x)$ represents the coefficient that describes the pattern of deviations from the age profile as k_t,
k_t represents the parameter that describes the change in overall mortality over time,
$b_2(x)$ represents the coefficient that describes the pattern of deviations from the age profile as $I(c)$,
$I(c)$ describes the change in mortality between generations,
$\varepsilon_{x,t,c}$ represents the random error term at time t.

3.7 Error Measurement

Stochastic modelling comparison uses error measurement to identify the best stochastic model with the minimal or least error. Error measurements serve as a means of assessing the effectiveness and accuracy of a model or system by quantifying the difference between the predicted values and actual values. This research utilises four error measures:

3.7.1 Mean Absolute Error (MAE)

$$MAE = \frac{1}{n}\sum_{i=1}^{n}|m_i - \widehat{m}_i| \tag{5}$$

Where:
n represents the number of observations,
m_i represents the actual value at time i,
$\widehat{m}_i$ represents the predicted value at time i.

3.7.2 Sum of Squared Error (SSE)

$$SSE = \sum_{i=1}^{n}(m_i - \widehat{m}_i)^2 \tag{6}$$

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Where:
m_i represents the actual value at time i,
$\widehat{m}_i$ represents the predicted value at time i.

3.7.3 Root Mean Squared Error (RMSE)

$$RMSE = \sqrt{\frac{\sum_{i=1}^{n}(m_i - \widehat{m}_i)^2}{n}} \tag{7}$$

Where:
m_i represents the actual value at time i,
$\widehat{m}_i$ represents the predicted value at time i,
n represents the number of observations.

3.7.4 Mean Absolute Percentage Error (MAPE)

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\frac{|m_i - \widehat{m}_i|}{m_i} \tag{8}$$

Where:
m_i represents the actual value at time i,
$\widehat{m}_i$ represents the predicted value at time i,
n represents the number of observations.

4. RESULTS AND DISCUSSION

4.1 Fitting the Stochastic Model

The LC model was used to compare the actual and fitted mortality rates for males and females, as shown in Fig. 1. Two curves are shown in both graphs: a red line representing fitted rates and a blue line representing actual mortality rates. The graphs for both genders indicate meagre and almost constant mortality rates up to the age of 40. For both actual and fitted data, there is a steady increase in mortality rates between ages 60 and 80, followed by a rapid spike. This trend becomes more pronounced after age 60, continuing to rise until age 80. The LC model successfully captures actual mortality trends, as evidenced by the close alignment of the fitted curves with the actual data for males and females across the age range.

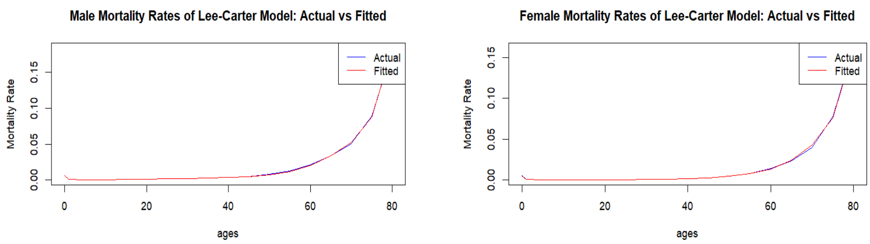

Fig. 1. Actual vs Fitted Mortality Rates for Males and Females Using the Lee-Carter Model

Fig. 2 illustrates the actual and fitted mortality rates using the BMS model for males and females ages 0 to 80. The x-axis represents age, while the y-axis shows the mortality rate ranging from 0 to 0.15. Blue lines denote actual mortality rates, and red lines denote fitted rates. The lines start near zero for both

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genders, indicating low mortality rates among younger age groups. The lines exhibit small variations and remain nearly flat and indistinguishable between ages 0 and 60. After age 60, both lines show a steep increase, reflecting age-related rises in mortality rates. The actual rates slightly exceed the predicted rates as individuals approach 80 years of age, leading to a minor divergence between the fitted and actual lines after age 60. The fitted models closely resemble the observed mortality rate patterns for both genders, showing a substantial increase in mortality rates with age, with only minor deviations. In summary, both graphs demonstrate that the fitted models accurately mirror the actual mortality rates, reflecting a similar upward trajectory with increasing age for both males and females.

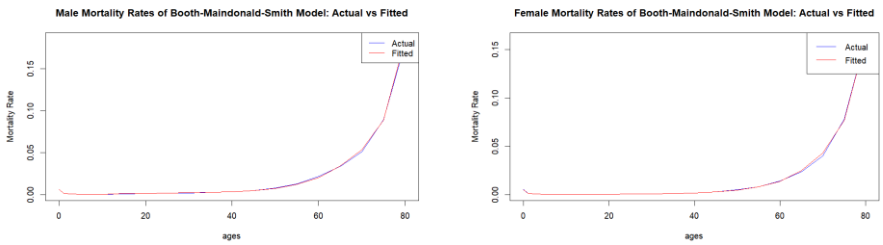

Fig. 2. Actual vs Fitted Mortality Rates for Males and Females Using the Booth-Maindonald-Smith Model

The APC model was applied to compare the actual and fitted mortality rates for males and females, as shown in Fig. 3. Both graphs feature two curves: a blue line representing actual mortality rates and a red line depicting fitted rates for both genders. The graphs show meagre and nearly constant mortality rates until age 60 for both males and females. After age 60, there is a sharp increase in mortality rates, with both actual and fitted lines rising steeply. The APC model fits the actual data well throughout the age range, albeit with noticeable deviations, mainly reflecting the pronounced increase in mortality rates in older age groups. In summary, both figures demonstrate that the APC model adequately mirrors the actual mortality rates, especially in capturing the upward trajectory with increasing age for both males and females.

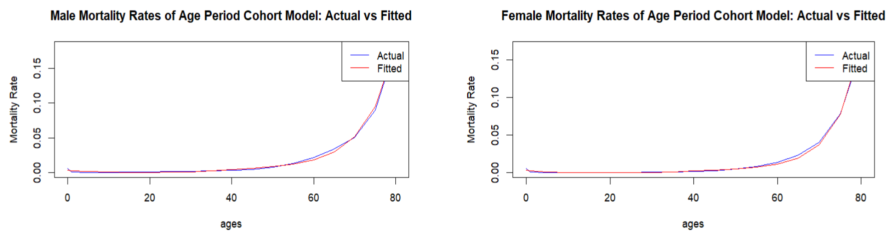

Fig. 3. Actual vs Fitted Mortality Rates for Males and Females Using the Age-Period-Cohort Model

4.2 Error Measurement Comparison

Based on Table 1, the LC model, among all the models considered, appears to offer the best fit for the mortality data for both genders, despite the BMS model's slightly lower MAPE for males, as evidenced by the values of RMSE, SSE, MAE, and MAPE. This comparison helps determine the most accurate model for predicting mortality rates, facilitating better-informed decisions.

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Table 1. Error Measurement Comparison

Error Measurements	Male			Female		
	LC Model	BMS Model	APC Model	LC Model	BMS Model	APC Model
RMSE	0.00114	0.00153	0.00329	0.00054	0.00087	0.00252
SSE	0.00047	0.00085	0.00389	0.00010	0.00027	0.00228
MAE	0.00055	0.00067	0.00182	0.00027	0.00035	0.00136
MAPE	5.30111	5.15026	60.7937	4.03881	4.05811	50.1408

4.3 Forecasting the Mortality Rates

Figure 4 illustrates the interpolated forecasted mortality rates for Malaysian males and females from 2021 to 2026, covering ages 0-80. The first graph shows that for males, mortality rates are forecasted to remain low in early age groups and increase steadily up to age 80. The projection indicates that death rates will remain stable over the next six years. The second graph depicts the forecasted rates for females, with mortality rates also expected to remain low early in life and rise with age. However, there is an anticipated decrease in mortality rates for ages 50 and above over the forecast period.

Both graphs reveal an exponential increase in mortality rates with age. Based on a 20-year history, the limited data restricts forecasts to the next six years. Despite the general upward trend, improvements in medical treatment and health awareness are expected to contribute to a decline in overall mortality rates in the future.

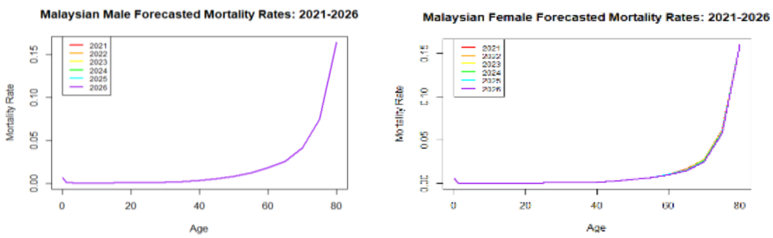

Fig. 4. Interpolated Forecasted Mortality Rates for Malaysian Males and Females (2021-2026)

5. CONCLUSION

This study aimed to fit and forecast mortality rates in Malaysia for both genders using the most effective stochastic model to improve public health planning and resource allocation. The study successfully fitted three stochastic models to Malaysia's mortality rates for both genders: the Lee-Carter model, the Booth-Maindonald-Smith model, and the Age-Period-Cohort model. The Lee-Carter model was determined to be the best model, as it produced the lowest measurement error. The study forecasted smoothed mortality rates from 2021 to 2026 using this model, interpolating from five-year to one-year age intervals to provide accurate projections. The study indicates that the probability of death increases with age due to several factors, including the emergence of diseases. Furthermore, improved access to medical treatment and increased awareness of maintaining a healthy lifestyle among the Malaysian community are cited as reasons why mortality among Malaysians is expected to decline in the future. Understanding these future trends enables better preparation for the specific needs of an ageing population and ensures the sustainability of social welfare initiatives.

Future research should focus on trends and model fits for individuals aged 40 and above, particularly in addressing variations observed in older age groups with the Booth-Maindonald-Smith and Age-Period-Cohort models. These findings provide valuable insights for insurers, policymakers, and public health

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officials, equipping them with essential information for informed decision-making and effective risk management.

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7. CONFLICT OF INTEREST STATEMENT

The authors agree that this research was conducted in the absence of any self-benefits, commercial or financial conflicts and declare the absence of conflicting interests with the funders.

8. AUTHORS' CONTRIBUTIONS

Shamshimah Samsuddin, Natasya Mazlan and Nur Aqilah Nadiera Nazhar carried out the research, wrote and revised the article. Nurul Akmar Mohamad Fadzill conceptualised the central research idea and provided the theoretical framework. Shamshimah Samsuddin designed the research, supervised research progress. Nurul Izzah Mohamad Naser anchored the review, revisions and approved the article submission.

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