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LUNG CANCER MORTALITY IN MALAYSIA THROUGH MORTALITY DYNAMICS MODELS

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ABSTRACT

Over the last several decades, lung cancer remains one of the most frequent causes of cancer mortality across the world with significant implications for public health planning. Accurate forecast of the mortality rate and life expectancy is necessary for guiding health care resources. This research aims to analyze the historical trend in lung cancer mortality rates, evaluate and compare the accuracy of the three mortality forecasting models; Lee Carter, Age Period Cohort (APC) and Cairns-Blake-Dowd (CBD), forecast lung cancer mortality rate from 2021 to 2031 and compute life expectancy at birth. The lung cancer mortality data for Malaysia covering from 2000-2020 year were extracted from Institute for health Metrics and Evaluation (IHME). In order to fit and test the models, data were split into training and testing sets. The model performing better was then considered to forecast up to 2031 and life expectancy were computed. The APC model demonstrated the best predictive performance, achieving the highest accuracy of Mean Absolute Percentage (MAPE), Mean Absolute Error (MAE) and Root Mean Square Error (RMSE). Based on APC model forecast, the baseline age effect demonstrated the expected rise in mortality rate with the age of the population. Beyond emphasizing the importance of strengthened public health efforts such as anti-smoking campaigns, early detection, and improve access to healthcare to enhance future longevity in Malaysia, these results also demonstrate the advantages of strong statistical modelling approaches in producing an accurate forecast in lung cancer mortality rates.

Keywords: *Age-Period-Cohort, Cairns-Blake-Dowd, Lee Carter, Life expectancy, Lung Cancer.*

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1. Introduction

Lung cancer is the primary cause of cancer-related fatalities in Malaysia, according to a more recent national-level assessment with a 5-year relative survival rate of just 11.0% (Rajadurai *et al*., 2020). The increasing trend in deaths due to lung cancer, particularly among older men, highlights the importance of robust, precise, and dependable models for forecasting cancer mortality to support healthcare planning and policymaking. Despite rapid progress in diagnostic and treatment technologies, the mortality rate due to lung cancer remains high, typically due to late diagnosis, lack of adequate screening programs, and ongoing exposure to such risk factors as smoking cigarettes and exposure to environmental poisons (Ji *et al*., 2023; Islam *et al*., 2024). In the case of Malaysia, there still lack adequate detailed studies that analyze long-term trends and forecasts of mortality rates due to lung cancer. Accurate mortality forecasts are essential to forecast future health needs, efficiently distribute resources, and design targeted public health intervention. In order to address these challenges, this study utilizes proven population models, namely the Lee-Carter (LC), Age-Period-Cohort (APC), and Cairns-Blake-Dowd (CBD) models, to analyze past trends and project future Malaysian lung cancer death rates from 2000 to 2031. Such traditional models offer interpretability, statistical adequacy, and transparency, which suit them best in data-constrained situations and require transparent information (Zulkifle *et al*., 2019, Wan Mohamad *et al*. 2024 and Basit *et al*. 2024). In addition, this study uses significant epidemiological indicators such as Age-Standardized Mortality Rate (ASMR) and Average Annual Percentage Change (AAPC) to quantify and plot mortality trends. These are critical measures in detecting striking changes in disease patterns as well as in producing trustworthy temporal and cross-population subgroup comparisons (Liaw *et al*., 2005) For model performance measurement, the conventional measures of standard error like Root Mean Squared Error (RMSE), Mean Absolute Error (MAE), and Mean Absolute Percentage Error (MAPE) are employed. Finally, life expectancy estimates are projected from the forecasted mortality rates, giving additional insight into the overall impact of lung cancer on public health. While life expectancy is a measure of public health progress, the research acknowledges its drawback and the growing need for counterpart indicators such as Disability-Free Life Expectancy (DFLE) and Healthy Life Expectancy (HLE) to reflect quality of life, especially among older populations (Egidi, 2008, Pisal *et al*. 2022, Muhammad Noor Mathivanan *et al*. 2025). This study contributes strength to the growing literature on the prediction of cancer mortality in Malaysia by applying established actuarial and demographic models to lung cancer mortality statistics. The findings will contribute to the evidence base for public health decision-making and cancer control and healthcare resource planning.

2. Methodology

2.1 Data Source

The Institute for Health Metrics and Evaluation (IHME) dataset on the risk of lung cancer death in Malaysia among individuals aged 5 to 84 from 2000 to 2020 is used in this study. It is simpler to perform in depth study on the influence of age and sex on the patterns over time when the data is separated by sex, year, and age groups at 5-year intervals. Age-Standardized Mortality rates (ASMRs) were calculated using the World Health Organization's (WHO) world standard population in order to standardize comparisons over time and between demographic groups. ASMRs indicate mortality rates per 100,000 people and account for shifts in the age distribution (Sung *et al*.,2021).

$$\text{ASMR} = \sum_i \left(\frac{\text{Deaths}_i}{\text{Population}_i} \times 100{,}000 \times \text{Weight}_i \right) \quad (1)$$

In epidemiological and public health research, this method is frequently employed to remove confounding brought on by disparate age distributions. The Average Annual Percentage Change (AAPC), which provides a single summary measure of the average rate of change during the research period, was also computed using Join point trend analysis to examine historical patterns in lung cancer mortality (Hasani *et al*., 2024). This enables the data's long term mortality trends and possible turning points to be identified.

2.2 Forecasting Models

Three well-established forecasting models like Lee-Carter, Age-Period-Cohort (APC) model, and Cairns-Blake-Dowd model (CBD) were used to forecast lung cancer mortality rates. Each of these models offers a different structure for capturing temporal changes and has been widely used in mortality forecasting literature. The Lee-Carter Model is expressed as follow:

$$\ln\left(m_{x,t}^{LC}\right) = \alpha_x + B_x k_t + \varepsilon_{x,t} \tag{2}$$

where

$m_{x,t}$: Lung cancer mortality rate at age x in year t
α_x : The average lung cancer log0-mortality at age x
β_x : the rate of change of mortality at age x relative to the time index k_t
k_t : Lung cancer mortality level index at time t
$\varepsilon_{x,t}$: Residual term for age x and year t with mean 0 and variance σ^2

The Age- Period-Cohort (APC) model extends the Lee Carter model by incorporating cohort effects. The formula is written as follows, whereby the additional coefficients

$$\log\left(\mathrm{m}_{\mathrm{x,t}}^{\mathrm{LC}}\right) = \alpha_{\mathrm{x}} + \beta_{\mathrm{x}}^{(1)}\kappa_{\mathrm{t}}^{(1)} + \beta_{\mathrm{x}}^{(2)}\gamma_{\mathrm{t\text{-}x}} + \varepsilon_{\mathrm{x,t}} \tag{3}$$

where

$\beta_x^{(1)}$: slope showing the trend of lung cancer mortality across different ages
$\kappa_t^{(1)}$: Age-specific sensitivity coefficient responding to time index index,
$\beta_x^{(2)}$: Age-specific sensitivity coefficient responding to cohort shifts x,
γ_{t-x^2}: cohort effect for year *t-x*, where t-x represents the birth cohort
$\varepsilon_{x,t}$: the residual term.

To resolve the linear dependency and identification problem among age, period, and cohort (C = P - A), we enforce the standard zero-sum and zero-slope constraints on the cohort parameter vector with identifiability constraint $\sum_t k_t = 0 \sum_x B_x = 1$. Cairns-Blake-Dowd (CBD) Model is expressed as follow:

$$\mathrm{logit}\left(\mathrm{m}_{\mathrm{x,t}}^{\mathrm{LC}}\right) = \mathrm{k}_{\mathrm{t}}^{(1)} + (\mathrm{x}\text{-}\bar{\mathrm{x}})\mathrm{k}_{\mathrm{t}}^{(2)} \tag{4}$$

where

$\mathrm{m}_{x,t}$: Lung cancer mortality rate at age x in year t
$\bar{x}$: The mean age of the population
$k_t^{(1)}$: The first time-related parameter
$k_t^{(2)}$: The second time-related parameter

The Cairns-Blake-Dowd (CBD) model was originally formulated to model higher-age mortality dynamics, where the logit transformation of death probabilities exhibits approximate linearity with age. In this study, while the dataset spans ages 5 to 84, applying CBD across the full age spectrum serves as an empirical benchmark to assess its boundary limitations on cause-specific cancer data. Because lung-cancer mortality in young cohorts (ages 5–49) is extremely low or zero, taking logit transformations of raw rates introduces mathematical instability. Estimation framework for sparse count CBD model calibration is expressed as follow:

$$D_{x,t}^{LC} \sim \text{Poisson}\left(E_{x,t} \cdot m_{x,t}^{LC}\right) \tag{5}$$

where $D_{x,t}^{LC}$ is the observed number of lung-cancer deaths and $E_{x,t}$ is the matching population exposure.

Furthermore, because the Cairns-Blake-Dowd (CBD) model assumes a linear logit mortality curve Eq. 2 designed specifically for higher ages, applying CBD across young age groups (ages 5–49) leads to substantial instability in parameter estimates. In the analysis, the CBD model specification is restricted strictly to older cohorts (ages 50–84), where its logit linearity assumption is demographically valid.

Age- specific intercept, time-varying mortality index, and age-specific sensitivity to that index are the three parts of the Lee-carter model, which breaks down the logarithm of the age-specific mortality rate (Lee and Carter, 1992). Singular Value Decomposition (SVD) was used for parameter estimates in accordance with accepted actuarial modelling procedures. Age effects (biological risk), period effects (external time-specific factors like diagnostics or policy), and cohort effects (shared experiences of birth cohorts) are the three temporal aspects that are included in the APC model. Log-linear Poisson regression, which is frequently used in APC analysis, was used in its implementation (Jahangiri *et al*., 2018; Cesare & Murphy, 2009).

The Bayesian Coherent Double-Gap (BCD) model integrates Bayesian hierarchical modeling with a coherent double-gap structure. It ensures consistency across sexes and regions while adjusting for uncertainty in long-term trends. The model accounts for mortality convergence and divergence using simulation-based inference (Booth & Tickle, 2011; Bai *et al*., 2023). Each model was fitted using the observed data from 2000 to 2020 and then used to forecast age and sex-specific mortality rates for the period 2021 to 2031.

2.3 Error Measures

Three prediction error measures, which are Mean Absolute Error (MAE), Root Mean Square Error (RMSE) and Mean Absolute Percentage Error (MAPE) was computed in order to assess model performance and choose the most accurate forecasting technique. Across all age groups and years, these symmetric measures evaluate the difference between predicted and actual mortality rates (Mubarik *et al*., 2020; Alijean & Narsoo, 2018). The best model for forecasting the future was determined to be the one with the lowest average errors across all three metrics.

MAE helps to determine the average magnitude of errors between the actual data and the model's forecasts, without considering whether the error is positive or negative. It is expressed as follow:

$$MAE = \frac{1}{n}\sum_{i=1}^{n} |y_i - \hat{y}_i| \tag{6}$$

To compute MAPE, the absolute error in each period is divided by the corresponding observed values, and the average of these calculated percentages is determined.

$$MAPE = \sum_{i=1}^{n} \frac{\left|\left(\frac{e_t}{y_t}\right)\times 100\right|}{n} \tag{7}$$

It provides one number that represents the magnitude of the prediction errors. RMSE can be particularly useful when to know how well a model predicts a continuous outcome. RMSE formula is as below:

$$RMSE = \sqrt{\frac{\sum_{i}^{n} (Y_t - \bar{Y}_t)^2}{n}} \tag{8}$$

2.4 Framework of Cause-Deleted Life Table

To assess the impact of lung-cancer mortality on overall population longevity, this study employs a competing-risk cause-deleted life table framework. Standard life expectancy at birth (e_0) cannot be computed directly from cause-specific mortality rates alone because lung cancer represents only one component of total population mortality. Furthermore, because our lung-cancer mortality dataset covers ages 5–84, calculating life expectancy at birth (e_0) involves accounting for all-cause infant and early childhood mortality (ages 0–4) along with the open-ended upper age interval (85+).

The official national all-cause life tables provided by the Department of Statistics Malaysia (DOSM) was chosen as our baseline. Let $m_{x,t}$ denote the baseline all-cause central death rate and $q_{x,t}$ denote the all-cause probability of dying between age x and $x + n$ in year t. The forecasted lung-cancer mortality rate is denoted as $m_{x,t}^{LC}$, where the superscript LC explicitly distinguishes cause-specific mortality from all-cause mortality. For ages $x < 5$, lung-cancer mortality is set to zero $m_{x,t}^{LC} = 0$), reflecting the extreme epidemiological rarity of lung cancer in in younger ages, including infants and young children.

To quantify the survival probability in a hypothetical population, via Chiang's cause-deleted life table method, the cause-deleted probability of survival $p_{x,t}^{-LC}$ (survival probability where lung cancer is completely eliminated as a cause of death) is expressed as

$$p_{x,t}^{-LC} = \left(p_{x,t}\right)^{1-R_{x,t}} \tag{9}$$

where $p_{x,t} = 1 - q_{x,t}$ is the baseline all-cause survival probability, and $R_{x,t}$ is the percentage of total mortality contributing to lung cancer at age x in year t

$$R_{x,t} = \frac{m_{x,t}^{LC}}{m_{x,t}} \tag{10}$$

The corresponding cause-deleted probability of dying is $q_{x,t}^{-LC} = 1 - p_{x,t}^{-LC}$. The cause-deleted person-years lived in the age interval (x, x+n) are calculated as

$$L_{x,t}^{-LC} = n \cdot l_{x,t}^{-LC} - a_x \cdot d_{x,t}^{-LC} \tag{11}$$

where $l_{x,t}^{-LC}$ is the survivor count at age $d_{x,t}^{-LC} = l_{x,t}^{-LC} . q_{x,t}^{-LC}$= is the number of cause-deleted deaths, $n = 5$ for five-year age intervals (n = 1 for single-year intervals), and a_x is the average fraction of time lived by those dying in the interval ($a_0 = 0.85$ for age 0; $a_x = 0.5$. n for $x > 1$). For the open-ended age interval (85+), person-years lived are closed using:

$$\Delta e_{x,t} = e_{x,t}^{-LC} - e_{x,t}^{\text{baseline}} \tag{12}$$

Because cause-specific mortality datasets frequently contain sparse or zero death counts ($D_{x,t} = 0$) in younger age groups (ages 5–24), logarithmic and logit crude-rate

transformations may encounter numerical instability or undefined outcomes. To resolve this, all three models are estimated within a Poisson count-based likelihood framework.

$$L_{85+,t}^{-LC} = \frac{l_{85+,t}^{-LC}}{m_{85+,t}^{-LC}}$$

The cause-deleted life expectancy at age x is then computed as

$$e_{x,t}^{-LC} = \frac{T_{x,t}^{-LC}}{l_{x,t}^{-LC}} = \frac{\sum_{y=x}^{85+} L_{y,t}^{-LC}}{l_{x,t}^{-LC}} \tag{13}$$

3. Result and Discussion

The historical patterns of lung cancer mortality are investigated under the first research objective using data collected. Males and females are graphed on separate graphs to reflect the differences and variations over time.

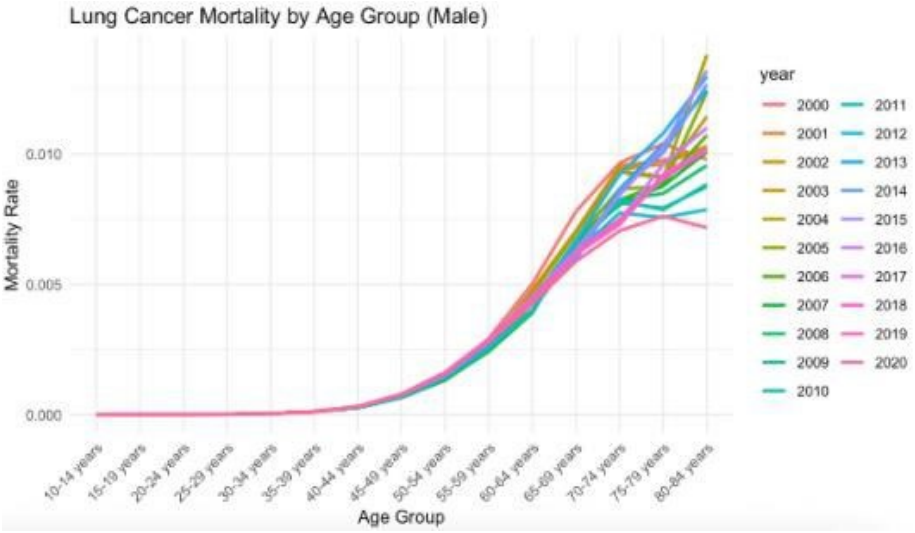


Figure 1(a). Lung Cancer Mortality Trends by Age Group (Male)

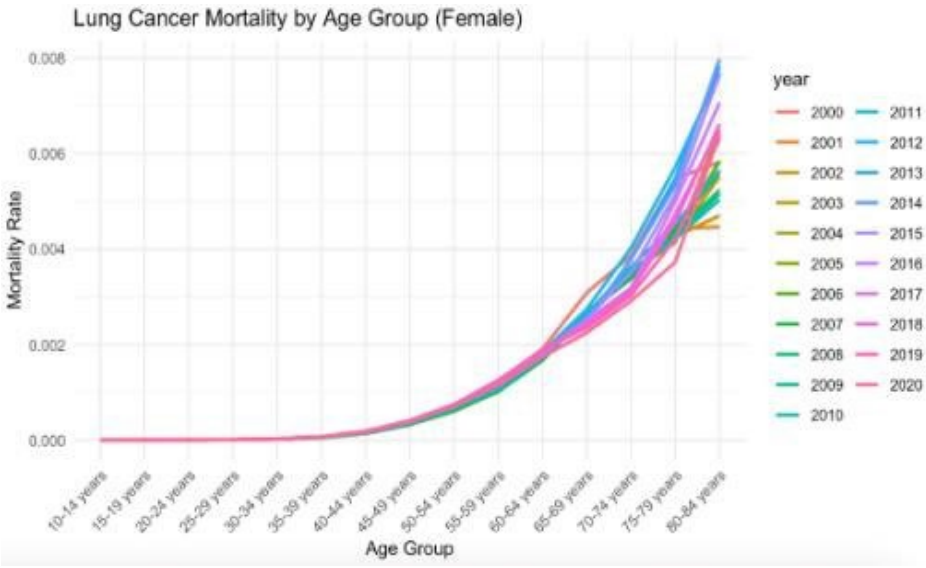


Figure 1(b). Lung Cancer Mortality Trends by Age Group (Female)

Figure 1(a) and Figure 1(b) illustrating lung cancer mortality by age group for males from 2000 to 2020 shows a strong upward trend in mortality rates as age increases. The mortality rate remains very low and nearly negligible among younger age groups, particularly those between 10 and 44 years. However, a sharp increase becomes evident beginning at the 45–49 years age group, with the most significant rises observed in those aged 60 years and above. The period from 2015 to 2020 shows a trend of stabilization or slight decline in mortality rates among the elderly, suggesting improvements in lung cancer management, earlier detection, or reduced exposure to risk factors in more recent years. Year-specific patterns are also clearly visible in the graph.

The graph for females presents a clear age-related increase in lung cancer mortality rates. Mortality remains extremely low or zero for younger females aged 10 to 44 years. A pronounced increase begins around the 50–54 years age group and continues steadily upward, peaking in the 80–84 years age category. This indicates that, like males, older females are at significantly higher risk of dying from lung cancer, though the overall mortality levels are lower compared to their male counterparts.

Table 1 shows the analysis of the Average Annual Percentage Change (AAPC) in lung cancer mortality rates by different age groups and by sex reveals extreme differences among trends across time. In women, several young age groups such as 15–19, 20–24, and 25–29 years have negative AAPC values indicating a declining trend in lung cancer death rate. The maximum decline is observed in the age group 15–19 years with an AAPC of 1.49%. Although with increasing age, the pattern tends to change in favor of positive AAPC values. Females between 35–39 to 60–64 years have a consistent rise in mortality, with the highest rise observed in the 80–84 years at 1.65% annually.

Table 1. AAPC in Lung Cancer Mortality by Age and Sex

Gender	Age Group	AAPC	CI Lower	CI Upper	Gender	Age Group	AAPC	CI Lower	CI Upper
Female	15-19	-1.49	-2.12	-0.85	Male	15-19	-1.67	-2.44	-0.9
	20-24	-0.55	-1	-0.1		20-24	-2.01	-2.48	-1.55
	25-29	-0.1	-0.45	0.26		25-29	-2.13	-2.47	-1.79
	30-34	1.02	0.72	1.32		30-34	-1.35	-1.71	-0.99
	35-39	1.62	1.38	1.86		35-39	-0.23	-0.5	0.04
	40-44	1.53	1.32	1.73		40-44	0.76	0.44	1.08
	45-49	1.29	1.15	1.43		45-49	0.87	0.62	1.12
	50-54	1.12	0.89	1.34		50-54	0.92	0.64	1.2
	55-59	1.04	0.72	1.37		55-59	0.53	0.15	0.91
	60-64	0.2	-0.1	0.5		60-64	-0.32	-0.82	0.18
	65-69	-0.82	-1.11	-0.54		65-69	-0.97	-1.21	-0.72
	70-74	-0.66	-1.2	-0.13		70-74	-1.29	-1.7	-0.87
	75-79	0.17	-0.7	1.05		75-79	-0.21	-0.99	0.59
	80-84	1.65	0.6	2.7		80-84	-0.43	-1.72	0.88

Table 2. Error Measurement for Male

Model	RMSE	MAE	MAPE
Lee-Carter	0.514	0.116	15.946
APC	**0.363**	**0.082**	**10.152**
CBD	0.829	0.180	493.891

Table 3. Error Measurement for Female

Model	RMSE	MAE	MAPE
Lee-Carter	0.450	0.205	10.773
APC	**0.272**	**0.126**	**6.438**
CBD	0.565	0.267	334.316

Based on Table 2 and Table 3 above, the AAPC model consistently outperformed the other models in both genders across all error measures with the lowest RMSE, MAE and MAPE values. The RMSE value for the APC model for males and females is the lowest compared to Lee-Carter and CBD models which are 0.363 and 0.272 respectively. The MAE value for the APC model is the lowest of the three models with values of 00.082 for males and 0.126 for females. Lastly, the MAPE value for the APC model is the lowest with MAPE of 10.152 males and 6.438 females. The selection of these metrics is grounded in established forecasting framework literature (Hyndman & Koehler, 2006; Mubarik *et al*., 2020), which emphasizes using a combination of scale-dependent and percentage-based measures to evaluate model performance comprehensively

The poor overall performance of the CBD model compared to LC and APC aligns with previous actuarial literature evaluating cause-specific mortality across wide age spans CBD lacks the parameter flexibility needed to fit both young and old cohorts simultaneously due to the a non-linear threshold jump around age 50 rather than a uniform logit-linear incline from age 5.

Figure 2 shows that the mortality rates are very low at younger ages for both males and females. The mortality rates start to shift sharply among elderly people after the age of 50. Male mortality rates are higher than female, among older men, the peaks mortality rates exceed 0.012 and for female, the peak rates are slightly above 0.006. This suggests that the lung cancer mortality rates for males are about twice as likely as females. Further, male death rates are more variable over the year, especially in the 65–80-year age group, while female mortality trends appear steadier and more predictable during the projection period, which must be remembered while computing life expectancy at birth on the basis of projected rates of death from lung cancer.

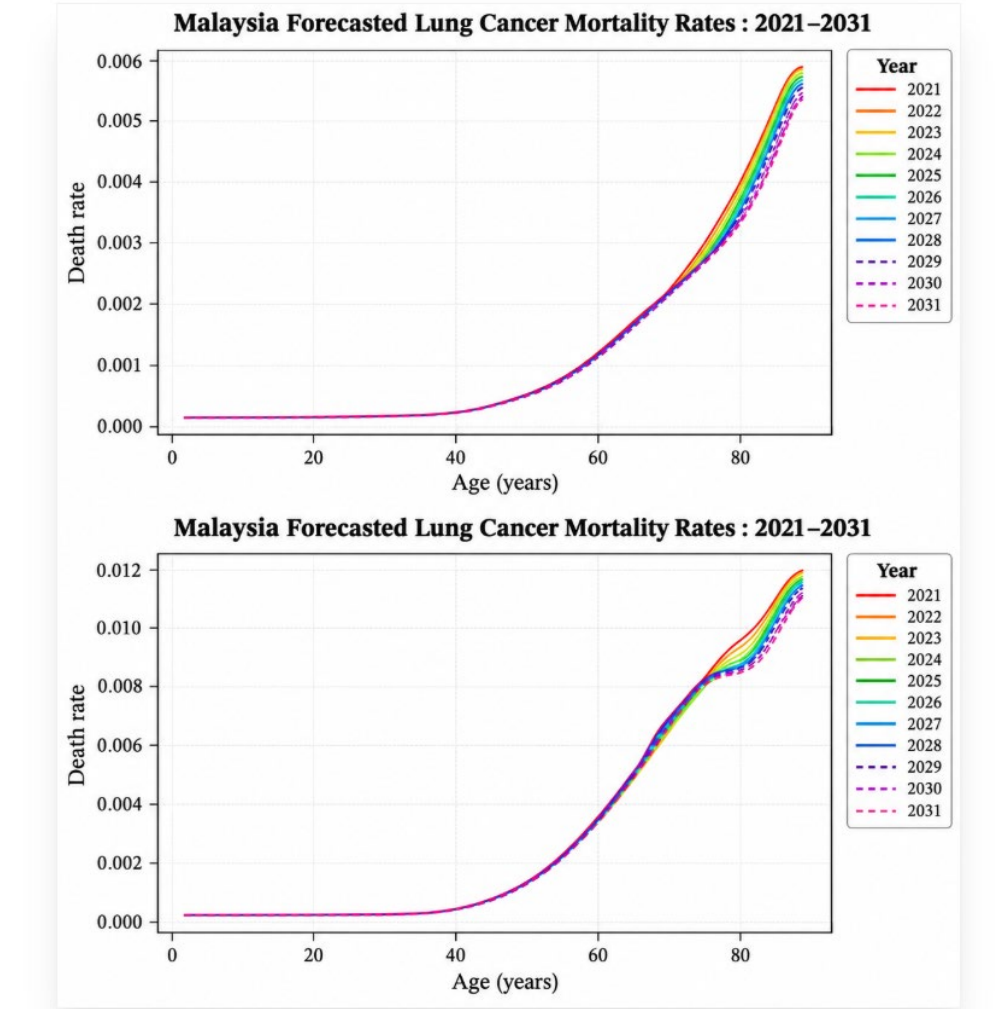


Figure 2. Forecasted Lung Cancer Mortality Rates in Malaysia (2021-2031) for a) Male and b)Female

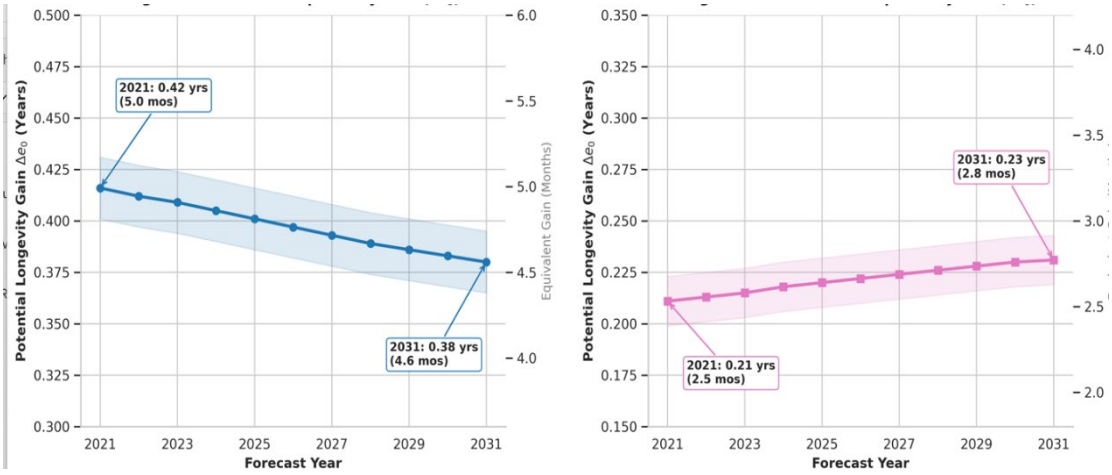


Figure 3. Forecasted Life Expectancy Gain, Male (left) and Female (right)

Figure 3 illustrates the potential gain in life expectancy at birth (Δe_{50}) if lung cancer were eliminated in Malaysia between 2021 and 2031, using a cause-deleted life table anchored on official all-cause mortality data. For Malaysian males, the potential longevity dividend starts at 0.42 years in 2021 and eases slightly to 0.38 years by 2031, which is a small contraction that occurs because baseline male lung cancer mortality is already projected to decline over the decade. For females, the gain remains virtually flat at 0.21 to 0.23 years, mirroring stable female mortality trends. Crucially, eliminating lung cancer yields nearly twice the longevity payout for men compared to women, proving that lung cancer prevention offers a disproportionately larger boost to male lifespan despite women having a higher overall population life expectancy. Rather than reporting absolute population life expectancy directly from lung-cancer rates, Table 4 presents the projected gain in life expectancy at birth (e_0) and at age 50 (e_{50}**)** resulting from the theoretical elimination of lung-cancer mortality in Malaysia.

Throughout the projection period (2021--2031), eliminating lung cancer benefits a larger longevity gain for Malaysian males than females, reflecting the higher baseline burden of lung cancer among men. In 2021, the potential gain in life expectancy at birth $e_0$is estimated at 0.42 years for males and 0.21 years for females. By 2031, based on the APC forecasted mortality trajectory, the potential life expectancy gain shifts to 0.38 years for males and 0.23 years for females.

At age 50 (Δe_{50}) where lung-cancer cases are predominantly observed, eliminating lung cancer adds approximately 0.35 years (4.2 months) of life to 50-year-old Malaysian males and 0.18 years to 50-year-old female patients. While lung cancer remains a critical cause of premature adult mortality, the results further support the observation that population lifespan is primarily driven by all-cause mortality drivers.

Together, these estimates indicate that the disparity in life expectancy between men and women will persist, with women living approximately 1.6 years more than men in the decade. The disparity suggests the need for gender-differentiated public health intervention. For women, continued investment in access to care and management of chronic conditions will be required to preserve positive trends in longevity. For men, enhanced prevention of lung cancer, focused anti-smoking policies, and improved screening programs can reverse stagnation in life expectancy.

4. Conclusion

This study analyses the historical trend in lung cancer mortality rate over 2000-2020 using ASMR and AAPC. Our results indicate that there was an increase in mortality by age in both genders and the highest rate was among the age group of 80-84 years. The rate of male declined significantly in ASMR and in AAPC, younger age groups of both genders showed a declining trend in rate of mortality while in middle-aged women the mortality rate increases.

To produce reliable future estimates, this study helps to identify the best fitting model for forecasting lung cancer in Malaysia. The three models: Lee carter, APC and CBD were contrasted based on performance error measure. The APC model presented the lowest error measure among other models, indicating it is the best model and provides a reliable approach to mortality forecasting. the APC model captures generational shifts in smoking habits and occupational exposures via its cohort term (γ_e), whereas LC lacks cohort tracking and CBD enforces a rigid two-parameter logit slope ill-suited for young age brackets Thus, we believe that APC model can be used to forecast the lung cancer mortality rate from 2021 to 2031. The result ensures an assured foundation upon which to forecast rate of mortality in the future and enables decision making in public health planning.

Across the entire forecast decade, Malaysian males stand to gain nearly twice as many months of life from lung-cancer elimination. While baseline national all-cause life tables show

that Malaysian females expect to live approximately 1.6 years longer than males overall, our cause-deleted analysis demonstrates that public health interventions targeting lung cancer offer a disproportionately larger longevity benefit for men, emphasizing the need for targeted male smoking cessation, workplace safety, and early screening programs

In conclusion, future research could expand the datasets to include demographic factors such as region and socioeconomic status to enhance forecast precision. Regarding other models, there are variety of alternative forecasting methods including machine learning which can even improve forecasting accuracy that could be explored in future works. This initiative will help bring a better risk assessment, improved life expectancy and better public health systems for coping with the rising lung cancer burden in Malaysia.

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Author Contribution

Suraya prepared the literature review and oversaw the article writing. Norkhairunnisa wrote the research methodology and performed fieldwork. Azizi conducted the statistical analysis and Juliana interpreted the results.

Declaration of generative AI in the writing process

During the preparation of this work, the author(s) did not use any AI-assisted technologies

Data Availability

Data sharing is not applicable to this article as no new datasets were generated or analysed during the current study.

Ethics Statement

The authors declare that this research did not involve human or animal subjects. All experimental procedures were performed following the institutional Safety, Health, and Environmental (HSE) protocols of Universiti Teknologi MARA.

Conflict of Interest

The authors have no conflicts of interest to declare.

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