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Analysing Causes of Death Mortality in Malaysia: A Lee-Carter Approach

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Abstract Understanding the causes of death mortality concerning aggregate trends is essential for comprehending a country's demographic health dynamics. Shifts in the leading causes of mortality can reveal significant insights that influence comprehensive mortality studies. This study examines changes in aggregate mortality and cause-specific mortality in Malaysia, using data from 2000 to 2019 sourced from the Department of Statistics Malaysia. The Lee-Carter (LC) mortality model is deployed to analyse aggregate mortality and mortality by cause of death. The research compares the fitted LC parameters, Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) values, and forecasted mortality rates for aggregate and cause-specific mortality. Results show that the time-varying indices exhibit diverse patterns, reflecting distinct trends for each cause of death compared to aggregate mortality. Notably, cause-specific mortality forecasts tend to be more pessimistic than aggregate forecasts, with marginally higher projected mortality rates. This comparative divergence arises due to the independent nature of each cause of death, proportional variations over time, and the characteristics of the forecasts across different age groups. These findings highlight the importance of cause-specific mortality data in providing deeper insights into Malaysia's mortality dynamics, which are critical for informing public health strategies and policy interventions.

Keywords Aggregate mortality; causes of death mortality; forecasting; Lee-Carter; Malaysia mortality.

Mathematics Subject Classification 62P05.

1 Introduction

Malaysia is confronting a significant demographic challenge. The decreasing mortality rates among older people have underscored the critical importance of accurate mortality table pro-

jections [1]. Moreover, Malaysian mortality is anticipated to undergo an epidemiological transition [2] due to shifts in the demographic structure driven by changes in the leading causes of death.

Between 2010 and 2016, notable mortality pattern changes were observed. For instance, HIV-related mortality decreased by over 50%, while deaths attributed to diabetes exhibited a marked increase from 15.2% to 17.5% of total deaths in Malaysia between 2011 and 2015 [3]. According to [4], ischemic heart disease remains the primary cause of mortality in Malaysia, with 115 deaths per 100,000 population recorded in 2019. Subsequent leading causes include lower respiratory infections (74 deaths per 100,000) and stroke (68 deaths per 100,000) population.

Multiple studies have identified a robust and reliable relationship between specific causes of death and overall mortality trends. [5] revealed that mortality improvements in the United States were primarily attributed to reduced deaths from major diseases and medical treatment advancements. Similarly, [6] discovered that the decline in cancer-related mortality between 1970 and 2000 played a crucial role in the overall decrease in mortality rates in the United States.

Investigating the link between causes of death and mortality has provided significant insights into mortality pattern complexities. [7] found that each cause of death follows distinct historical trajectories, resulting in varied changes. These trend variations are anticipated to influence future mortality, particularly among older population segments, substantially. Researchers have extensively utilised time-series data to model causes of death and analyse emerging trends, as demonstrated in studies by [8–11]. Additionally, mortality forecasting using country-specific causes of death data has been employed by researchers such as [12–14].

Understanding the role of cause-specific mortality in shaping mortality trends is essential for accurate mortality modelling and forecasting. A robust human mortality model relies on this comprehensive understanding to ensure precise estimations and predictions. Accurate mortality forecasts provide substantial value to various stakeholders: they enable governments to maintain sustainable pension provisions and assist insurers in setting appropriate policyholder premiums. The information gleaned from the cause of death data enriches our knowledge of mortality development, serving as a cornerstone for further advancements in understanding changes in mortality. By analysing trends in causes of death, researchers can gain valuable insights into future mortality rate patterns. This enhanced understanding allows for better preparation and response to changes in population health dynamics.

The Lee-Carter (LC) model, introduced by Ronald D. Lee and Lawrence Carter in 1992 to model and forecast mortality in the United States [15], employs two primary elements; age and year, in mortality projection. Since its inception, this model has been widely adopted and extended by researchers globally to improve mortality rate forecasting.

Numerous researchers have utilised extrapolative methods, such as the LC model and its extended versions, to study cause-specific mortality. These approaches typically assume the independence of each cause of death. Research by [10,16,17] has focused on studying mortality changes by examining historically grouped causes of death data. Some models incorporate latent factors representing mortality rate trends across periods or cohorts, providing insights into relationship explanations based on their variance [18]. The results from extrapolative methods such as the LC model allow researchers to identify significant patterns and anomalies exhibited by causes of death.

The LC method has encountered challenges, including long-term mortality rate convergence [19–21] and identifiability problems [22–24]. These challenges impact the accuracy of long-term mortality forecasts, particularly when multiple forecasts are combined [25]. Consequently, researchers have extended the LC model to incorporate cause of death information for more comprehensive mortality pattern analysis. For instance, a study by [10] analysed 11 causes of death influencing mortality progression, extending the classic LC paradigm to a multivariate LC model to refine cause-specific mortality modelling.

This research presents the initial analyses of mortality modelling by adopting the LC model [15] to forecast aggregate and cause-specific mortality in Malaysia. Aggregate mortality represents total mortality across all causes, while cause-specific mortality segregates the mortality experienced by individual causes. The cumulative cause-specific mortality will provide a comprehensive overview of aggregate mortality trends. Subsequently, the forecasted mortality rates from both aggregate approaches and by each cause of death are analysed for better estimation and understanding of Malaysia's forecast trends and nature.

2 Data

Causes of death are systematically recorded using the International Classification of Diseases (ICD) [26], specifically the ICD-10 version. As a globally adopted system, the ICD is regularly updated to reflect scientific and technological advancements, enabling more precise cause-of-death classifications. Various data sources widely utilise this comprehensive system for coding and classifying information from death certificates [27].

Recognising the potential variations in cause-of-death reporting, the WHO, in collaboration with 10 international centres, developed ICD standards to ensure consistency and comparability in global mortality statistics. Each cause of death receives a specific code, facilitating standardised recording and analysis across different countries.

Research has demonstrated that excessive granularity in cause-of-death categorisation can complicate accurate prediction. As highlighted by [16], focusing on a limited number of cause groups that demonstrate sufficiently varied patterns to illuminate key challenges and potential solutions is more effective while discussing mortality. Consequently, the current study carefully references country-specific data to determine appropriate ICD groupings. The fundamental challenge for most countries, however, is that cause of death data are often unavailable or subject to substantial problems of comparability.

This research utilises Malaysian age, sex, population, and cause-specific death data by ICD-10 code from 2000 to 2019, obtained from the Department of Statistical Malaysia (DOSM) [28]. It is important to note that the dataset is relatively constrained, representing the only available recorded data from DOSM.

The DOSM data follows a detailed age group structure based on interval ages: 0, 1-5, 6-10, 11-15, 16-20, 21-25, 26-30, 31-35, 36-40, 41-45, 46-50, 51-55, 56-60, 61-65, 66-70, 71-75, 76-80, 81-85, 86-90, and 90+.

Following methodologies employed in previous studies [8,9], this research categorises causes of death into 10 main categories that collectively account for more than 80% of total deaths. Each category represents a compilation of related death classifications based on ICD-10 coding.

Table 1: Causes of Death Categories.

Main Causes of Death	**Examples of Common Diseases**
Circulatory Diseases	Ischemic heart disease cerebrovascular disease
Respiratory Diseases	Pneumonia, influenza, respiratory diseases (asthma, bronchitis, etc.)
Neoplasms (Cancer)	Lung, colon, breast, prostate, and related cancer diseases
Infectious Diseases	Gastroenteritis, tuberculosis, HIV, viral fever, bacterial diseases
Septicaemia Diseases	Deaths due to septicaemia
Transport Accidents	Deaths from vehicle-related accidents
All External injury	Deaths due to injuries, excluding transport accidents
Diabetic Diseases	Deaths related to diabetic
All Other diseases	Mental health conditions, meningitis, Alzheimer's, and other unclassified conditions
Old Age Senility	Deaths of individuals 65 and above

World Health Organization (https://www.who.int/standards/classifications/classification-of-diseases)

3 Methods

3.1 Death Data Calculation

The death count data for each category is calculated using the following equation:

$$d_{t,x} = \sum_{allj} d_{t,x,j} \tag{1}$$

where,

- $d_{d,t}$ represents the total death count for all causes at age x in year t
- $d_{t,x,j}$ represents the death count for age x in year t due to cause j.

The central death rates are computed as follows:

$$m_{t,x,j} = \frac{d_{t,x,j}}{E_{t,x}} \tag{2}$$

where,

- $m_{t,x,j}$ represents the central death rates for age x in year t due to cause j
- $E_{t,x}$ is derived from the number of survivors at the age x for time t

3.2 Lee Carter Model

The Lee & Carter (1992) model specifies that a linear relationship between the natural log of central mortality, age, and year:

$$ln(m_{x,t}) = \alpha_x + \beta_x \cdot \kappa_t + \epsilon_{x,t} \tag{3}$$

where,

- $m_{x,t}$:Central death rate at age x in year t.
- α_x:Average age of log-mortality
- β_x:Sensitivity of the log-mortality to changes
- κ_t:Mortality index
- $\epsilon_{x,t}$:Error term.

Singular Value Decomposition (SVD) is a mathematical technique for decomposing the mortality data matrix into its principal components. This approach enables the identification of key patterns and trends that might not be immediately apparent, thus enhancing the accuracy and interpretability of the mortality forecasts and providing a more nuanced understanding of mortality dynamics in Malaysia from 2000 to 2019 [15].

Parameters β_x and κ_t are derived from the first left and right singular vectors:

$$\kappa_t = u_t s \sum_{x=0}^{\omega} v_x \quad \text{and} \quad \beta_x = \frac{v_x}{\sum_{x=0}^{\omega} v_x} \tag{4}$$

where,

- $v_x$is the first right singular vector of ages of the SVD
- u_t is the first left singular vector of years
- s is the most prominent singular value

For multiple causes of death, the model is extended to:

$$ln(m_{x,t}^{cause \quad j}) = \alpha_x^{cause \quad j} + \beta_x^{cause \quad j} \kappa_t^{cause \quad j} + \epsilon_{x,t} \tag{5}$$

where,

- $m_{x,t}^{cause \quad j}$ is the central death rate with age x for a specific cause of death j in year t
- $\alpha_x^{cause \quad j}$ iis the average age of log mortality for a specific cause of death j
- $\beta_x^{cause \quad j}$ is the sensitivity of the log mortality to changes $\kappa_t^{cause \quad j}$ for a specific cause of death j.

The $\kappa_t^{cause\quad j}$ is the measure of mortality index for a specific cause of death j, and $\epsilon_{x,t}$ is the error term. The mortality rates for aggregate and by causes of death can be forecasted by predicting the values of κ_t. The κ_t is forecasted using an Auto-Regressive Integrated Moving Average (ARIMA) model, specifically ARIMA (0,1,0), which corresponds to a random walk with drift, is used. This specific ARIMA model can be expressed as:

$$\kappa_t = \kappa_{t-1} + \epsilon_t \tag{6}$$

where,

- κ_t is the mortality index at the time t,
- κ_{t-1} is the mortality index at the time $t-1$
- ϵ_t is a white noise error term with mean 0 and constant variance.

Using the forecasted values of the κ_t, the projected future mortality rates can be found using the formula in (3) by reverting to the actual mortality. The log death rates need to be exponentiated as:

$$m_{x,t} = \exp(\alpha_x + \beta_x \cdot \kappa_t + \epsilon_{x,t}) \tag{7}$$

and for cause-specific death is given as:

$$m_{x,t}^{cause\quad j} = \exp(\alpha_x^{cause\quad j} + \beta_x^{cause\quad j}\kappa_t^{cause\quad j} + \epsilon_{x,t}) \tag{8}$$

The AIC and BIC compare models for aggregate and cause-specific data in analysing the LC model fitting. These criteria help evaluate the trade-off between model complexity and explanatory power, guiding the selection of the model. It can be defined as:

$$BIC = -2lnL + klnN \tag{9}$$

$$AIC = -2lnL + 2k \tag{10}$$

where,

- N: Number of samples
- L: Log-likelihood function
- k: Number of estimated parameters

All calculations were performed using R Studio software, utilising the demographic and StMoMo packages.

4 Results and Discussion

4.1 Aggregate and Causes of Mortality Analysis

The overall Malaysian mortality rates, as depicted in Figure 1, have generally increased steadily over the years. The graph illustrates that the number of deaths per population unit has increased incrementally. Specifically, by 2019, the mortality rate reached 0.00544, rising from its initial value of 0.00434 in 2000.

Figure 1: Malaysian Overall Mortality Rates by Years.

While data is available from 2000 to 2019, only the years 2000, 2010, and 2019 are presented in the figures. This selection was made to simplify the visualisation, allowing for a more explicit comparison of key trends over time without compromising the overall insights provided by the entire dataset. Specifically, Figure 2 shows the Malaysian mortality rates for 2000, 2010, and 2019, plotted against age. The mortality rates are very low at younger ages and increase sharply with older ages, and these groups generally experience higher mortality rates due to age-related health challenges. The trends in mortality for all three years show minimal difference for those aged 65 and below. However, for ages 65 and above, the 2019 curve lies below the 2000 and 2010 curves, indicating mortality improvements for the older population as years pass. Notably, the trend suggests that mortality rates may continue to increase.

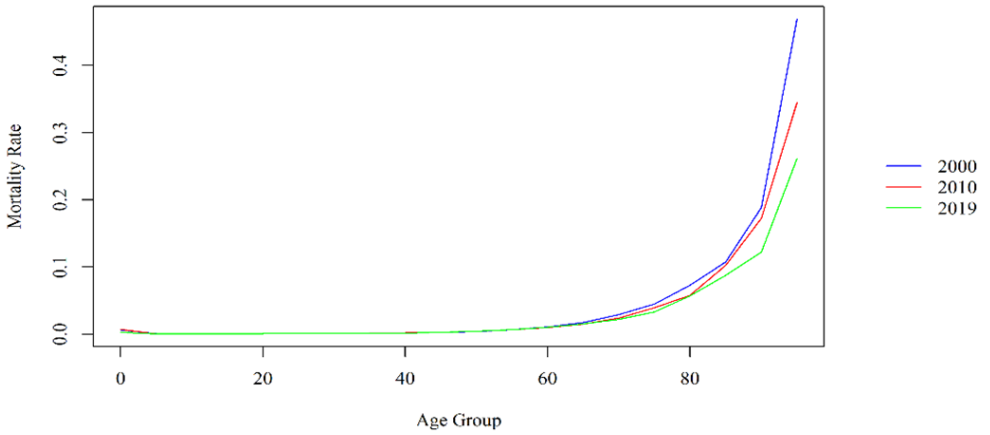

Figure 2: Malaysian Aggregate Mortality Rates for Years 2000, 2010, and 2019 by Age Groups.

Figure 3 displays the number of deaths by various causes over 2000, 2010, and 2019. Each cause of death is represented by a colour-coded bar for each year. Notably, circulatory diseases consistently contribute the highest number of deaths across all three years, followed in frequency by respiratory and neoplasm diseases. The data also demonstrates a significant rise in the number of deaths over the years across all causes, with particularly notable increases in circulatory, respiratory, neoplasms, and other conditions. Furthermore, deaths due to diabetes and septicaemia have also increased, reflecting persistent challenges in managing these conditions. A critical observation is the increase in deaths due to old age over the years, which likely indicates the growing proportion of elderly deaths within the population.

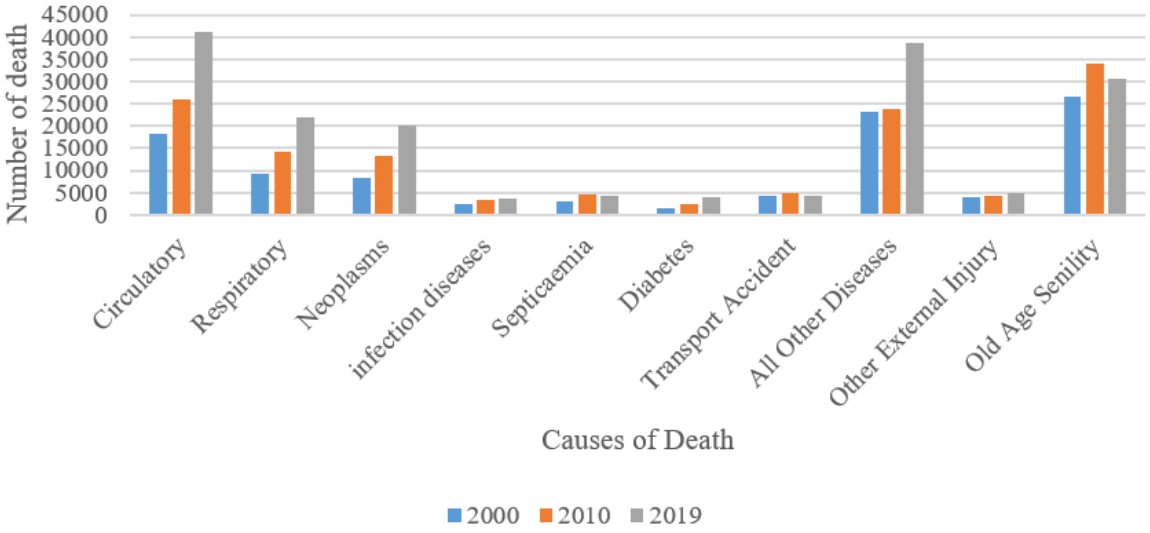

Figure 3: Number of Death by Causes for Years 2000, 2010, and 2019.

Figure 4 illustrates the average mortality rates across age groups in Malaysian populations for various causes of death. Notably, all causes exhibit an upward trend in mortality rates

with increasing age. Specifically, old age shows the most significant rise in mortality rates, emphasising its prominence as a major cause of death among the elderly. Circulatory diseases and neoplasms also demonstrate substantial mortality rate escalation, underscoring their critical impact on older populations. Respiratory, infectious, and diabetes-related diseases show gradual increases in mortality rates at older ages, though at lower levels compared to circulatory and neoplasm diseases. Additionally, septicaemia displays a rising trend but remains relatively lower than other major causes. Importantly, transport accidents and other external injuries have the lowest mortality rates, with only slight increases in older age groups.

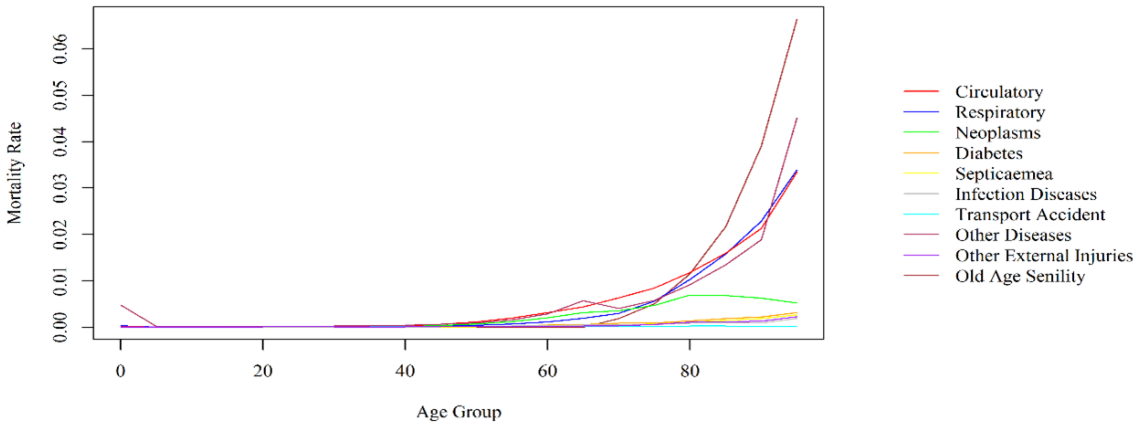

Figure 4: Malaysia Average Mortality Rates by Cause of Death.

4.2 Lee-Carter Parameter Estimation

The LC parameter estimation in Figure 5 provides insights into mortality trends across ages and over time. In the LC model, the α_x vs x parameter representing the baseline mortality rate, increases with age, indicating that log mortality rates rise as individuals age. The β_x vs x parameter, showing age-specific sensitivity to overall mortality trends fluctuates but generally remains above zero, suggesting that certain age groups are more susceptible to changes in mortality trends, especially those between 40 and 80 years. The κ_t vs t parameter, tracking the time-varying mortality index, shows a declining trend over the years. These parameters provide a comprehensive view of mortality variations by age and temporal changes.

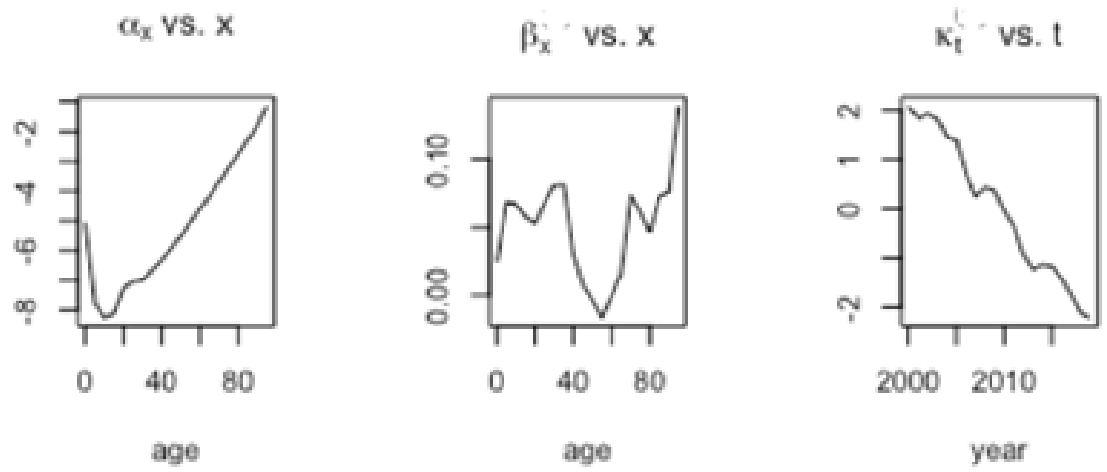

Figure 5: Parameters for LC Fitted to Malaysia Population Data.

Figure 6 displays fitted mortality rates on a logarithmic scale across different ages. The x-axis shows 0 to 90 years of age, and the y-axis represents the log death rate. Initially, the log death rate is high at birth, sharply decreasing through early childhood and reaching a minimum that reflects reduced neonatal risks. In contrast, low childhood mortality rates suggest effective early healthcare interventions. A slight increase is observed in young adulthood, possibly due to elevated mortality rates from transport accidents, followed by a steady rise through adulthood with a significant increase post-age 60. The exponential rise in death rates from age 20 onwards highlights the impact of age-related diseases. Consistent trends of fitted rates across various cohorts indicate the consistency and robustness of these patterns.

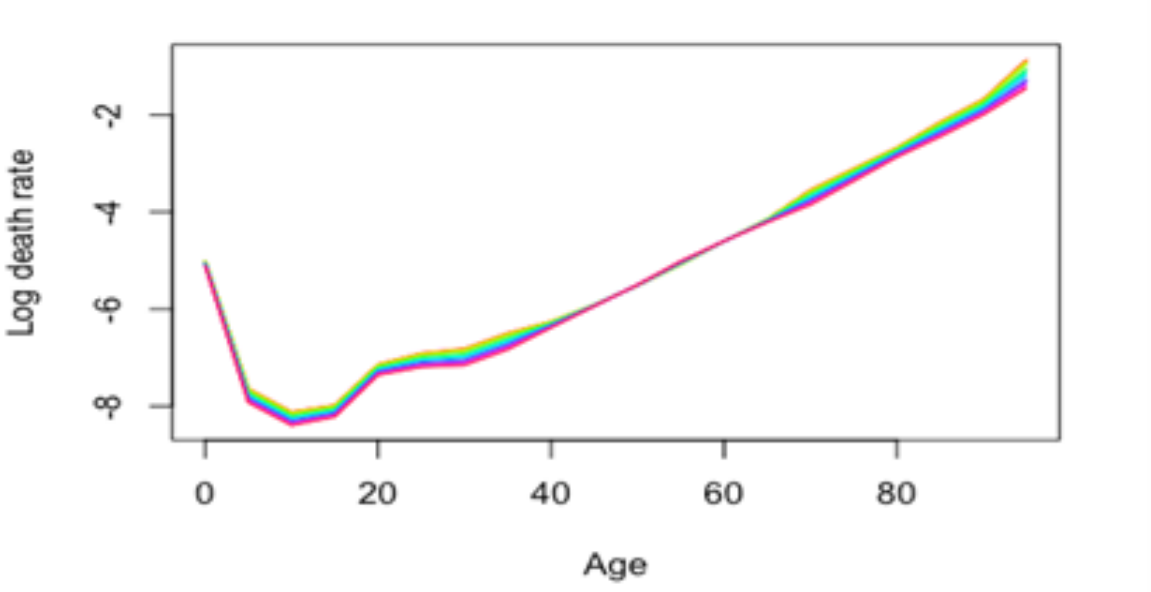

Figure 6: LC Fitted Rates of Log Death Rate Against Age.

The LC parameter estimates for each cause of death, as shown in Figures 7, 8, and 9, exhibit a high degree of consistency, particularly in the behaviour of α_x against age (x). The α_x

parameter in the LC model represents the age-specific baseline mortality rate, capturing how the underlying risk of mortality varies across different age groups and cause-specific mortality. The estimates forα_x generally increase with age across all diseases, reflecting the natural progression of mortality risk with ageing. However, an exception is observed in non-disease-related causes such as transport accidents and other external accidents, where theα_x parameter begins to decline at an earlier age of 20, possibly indicating a different risk pattern associated with these sudden and accidental causes.

Similarly, the β_x parameter estimation for each cause of death against age (x) shows an upward trend curve. In the LC model, the β_x parameter captures the age-specific response to time-varying mortality trends, reflecting how different age groups are differentially affected by changes in overall mortality. This indicates increasing sensitivity to mortality risks with age, which is more pronounced in major diseases. For most diseases, the sensitivity rises significantly at older ages, consistent with the growing prevalence and impact of age-related health issues. However, exceptions include causes such as transport accidents, other external causes, and diabetes, which exhibit distinct mortality patterns. For these causes, there is a notable concentration of deaths occurring before age 60, which affects the overall parameter estimates and highlights the unique demographic and epidemiological factors influencing mortality in these categories.

In contrast, the κ_t parameter displays an upward movement against age (x) over time for most causes, indicating a temporal increase in mortality rates associated with those conditions. In the LC model, the κ_t parameter represents the time-varying component of mortality, capturing overall temporal trends in mortality rates across different causes of death. Infectious diseases showed a significant spike around 2018-2019, while causes such as circulatory diseases and neoplasms steadily increased over the years. The consistent rise in κ_t values for key causes such as circulatory diseases and neoplasms highlights their significant contribution to overall mortality. However, exceptions are observed for septicaemia and old age senility. The downward trend for septicaemia suggests improvements in mortality outcomes over time, likely due to advancements in medical treatments and infection management. On the other hand, the pattern for old age senility reflects its focus on deaths occurring exclusively at age 65 and above, where trends are less affected by broader age groups and are more concentrated among the elderly population. This analysis highlights the varying sensitivity of the LC model parameters across different causes of death, emphasising the importance of age-specific and time-specific factors in understanding mortality trends.

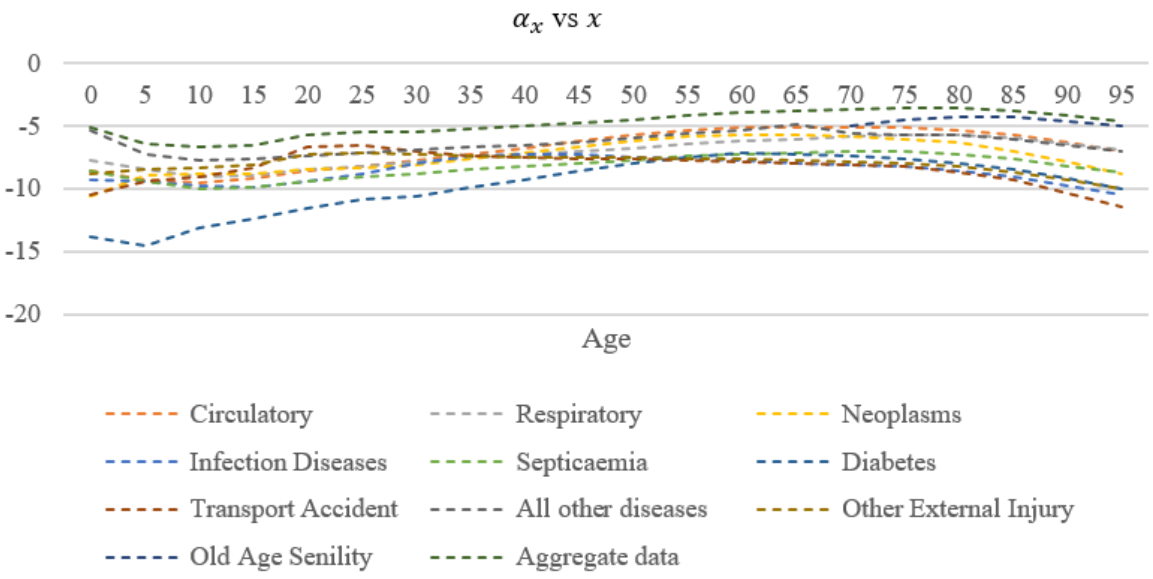

Figure 7: LC Fitted for α_x vs x.

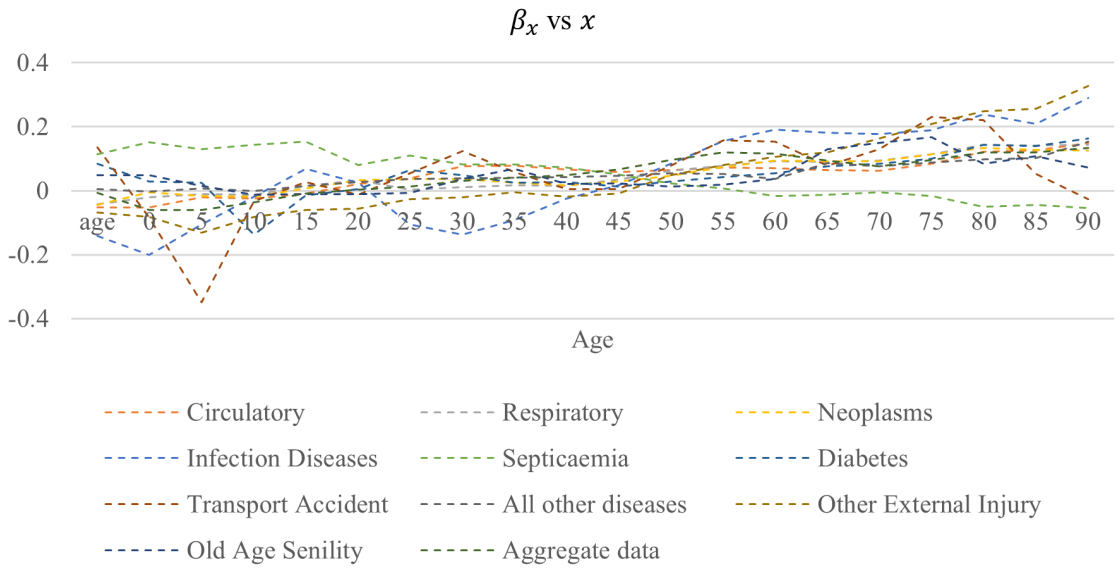

Figure 8: LC Fitted for β_x vs x.

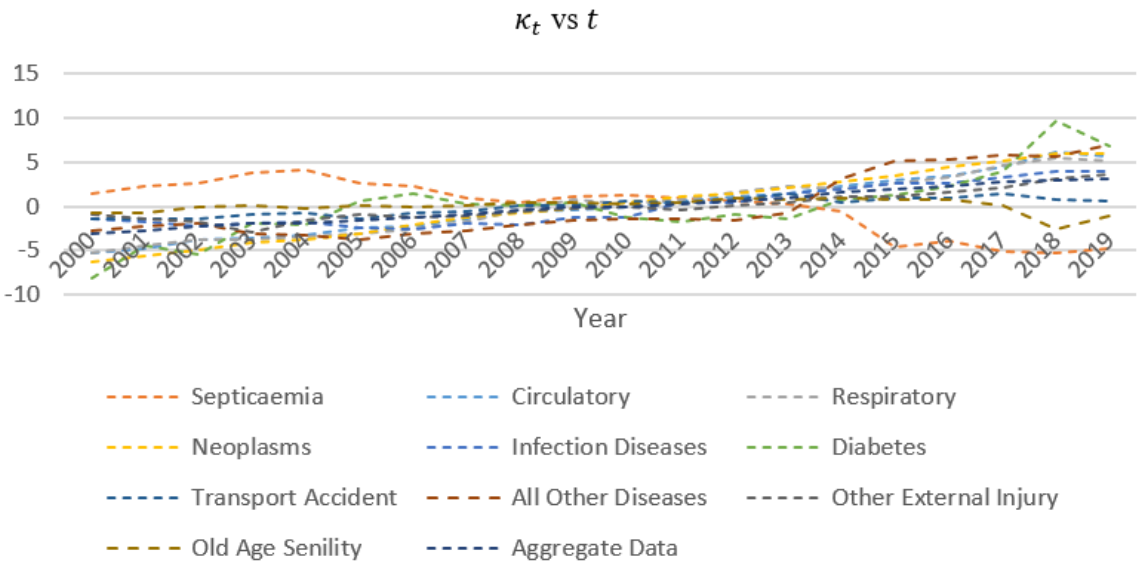

Figure 9: LC Fitted for κ_t vs t.

The AIC and BIC values are generated based on the LC model fitted for each cause of death. Table 2 presents these values, which are used to compare the relative suitability of the model across different causes. Lower AIC and BIC values indicate that the LC model provides a better trade-off between complexity and explanatory adequacy for a particular cause. Specifically, causes such as transport accidents, neoplasms, and infectious diseases have the lowest AIC and BIC values (e.g., Transport Accidents: AIC = 3473.433, BIC = 3704.938), suggesting that the LC model is relatively more appropriate for these causes compared to others. In contrast, circulatory diseases, respiratory diseases, and diabetes have higher AIC and BIC values, reflecting slightly more complex mortality trends. The mortality category has the highest AIC (10278.3) and BIC (10509.81) values, indicating more complexity in modelling overall mortality trends. Likewise, causes such as old age senility and all other diseases have notably high AIC (7324.606, 7683.637) and BIC (7556.111, 7915.142) values, pointing to more significant variability or irregular patterns in their mortality trends.

Table 2: AIC and BIC for LC Model Fitted.

Cause of Death	**AIC**	**BIC**
Circulatory	6044.528	6276.033
Respiratory	4661.791	4893.296
Neoplasms	3786.761	4018.266
Infection Diseases	3796.975	4028.48
Septicaemia	3964.332	4195.837
Diabetes	5034.6877	5266.192
Transport Accidents	3473.4337	3704.938
All Other Diseases	7683.637	7915.142
Other External Injuries	3789.3277	4020.832
Old Age Senility	7324.606	7556.111
Aggregate	10278.3	10509.81

4.3 Aggregate Death and Causes of Death Mortality Forecasting

The LC parameter estimation analysis was applied to project mortality rates from 2000 to 2019, examining overall and cause-specific trends. By aggregating mortality rates across different causes of death, the analysis provides a comprehensive view of projected mortality patterns. The forecasted mortality rates for each cause of death are summed together and serve as the basis for comparing with forecasted aggregate mortality rates. Figure 10 presents the forecasted aggregate mortality rates for different age groups for 2020, 2030, and 2039. The pattern suggests a general decline in mortality rates over time, particularly for older individuals. However, for the older age groups (60+ years), the mortality rates increase more steeply with age, showing noticeable differences between the years. The mortality rates are highest in 2020, followed by 2030, and then 2039, reflecting a projected reduction in mortality rates over time for older age groups.

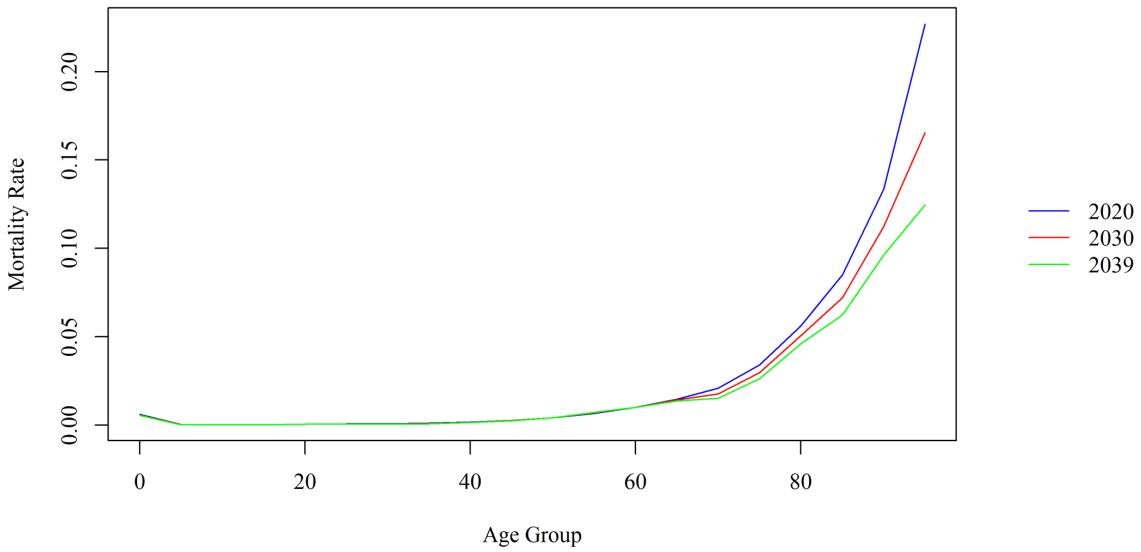

Figure 10: Forecasted Aggregate Mortality Rates.

Figure 11 displays the forecasted sum of each cause of death mortality rate by the different age groups for the selected years of 2020, 2030, and 2039. At younger ages, between ages 0 and 40, the mortality rates are very low and show stable mortality rates across all three years. For people in the age range of 40 to 60, mortality rates begin to rise, reflecting the onset of age-related risks and causes of death. The three lines (2020, 2030, 2039) remain relatively close together, indicating slight variation in the forecasted mortality rates for this age group. Mortality rates rise sharply after age 60, with the steepest increases beyond age 70. These rising mortality rates likely reflect the cumulative impact of chronic diseases, reduced physiological resilience, and increased vulnerability to complex health conditions that typically emerge in later life. The difference between years becomes more pronounced as people get older, with higher mortality forecasted for 2030 and 2039. This suggests that improvements in healthcare, technology, or preventive measures will have the most impact on older populations.

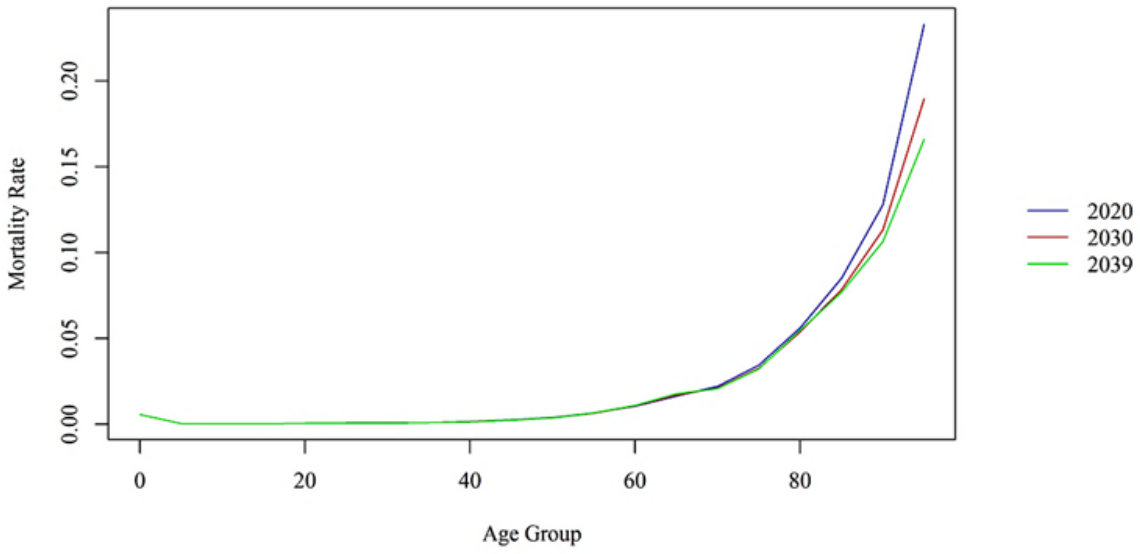

Figure 11: Forecasted Mortality Rates by Causes of Death.

A deeper analysis shows that the forecasted values of the aggregate mortality rates are slightly lower than those calculated by summating all causes of death. These discrepancies may arise from variations in data collection methods, differences in how specific causes of death are categorised, or the complex interactions between multiple health conditions in older populations. These findings are in line with Wilmoth (1994). These findings align with Wilmoth's (1994) seminal work, highlighting the nuanced differences between aggregate and cause-specific mortality forecasting approaches. The cause-specific death forecasts produce more pessimistic mortality rates as compared to aggregate deaths. The gap between the forecasted data is further examined closely in Figure 12. The graph illustrates the average of 20-year forecasted mortality rates by each age group for aggregate and cause-specific deaths from 2020 until 2039. Average differences between the aggregate forecasted rates and the summation of all causes forecasted rates are presented. As can be seen from the graph, the differences are becoming more apparent, specifically for the age group 60 and above. This suggests that applying aggregate forecasted mortality rates might underestimate the risk of death.

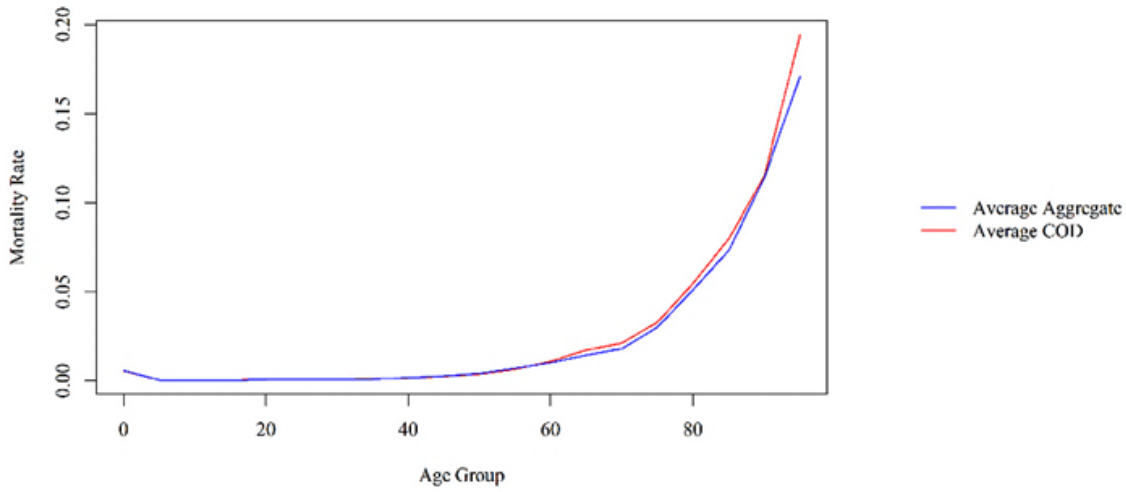

Figure 12: Comparison Between Average Aggregate Against Average Sum of Causes of Mortality Rates.

The calculated mortality difference between the average forecasted aggregate and the average forecasted sum of causes of death in Figure 13 for selected age groups shows there is no difference for age groups between 0 and 60. However, the difference becomes noticeable for ages more than 60 years.

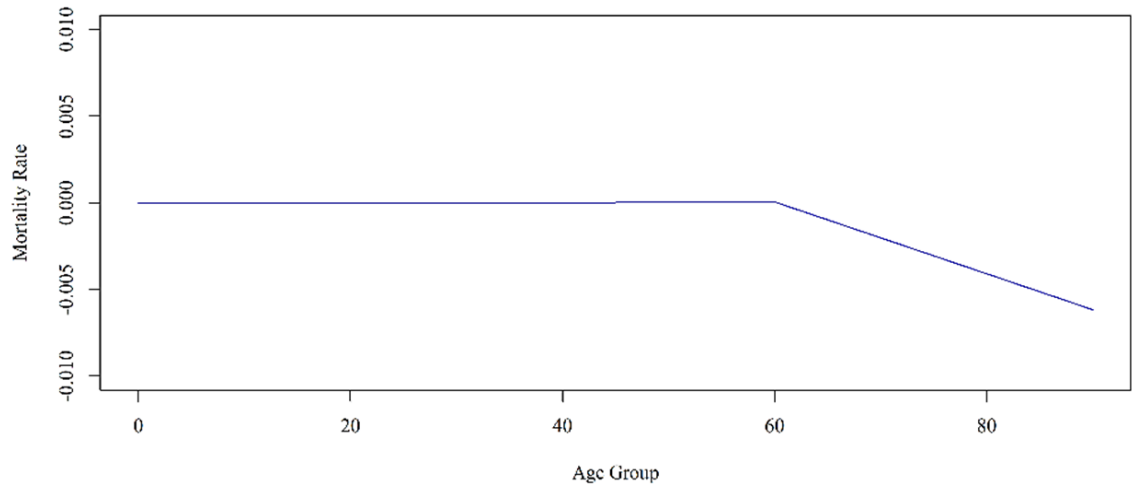

Figure 13: Differences Between Average Aggregate and Average Sum of Causes of Mortality Rates.

5 Conclusion

The mortality forecasts by cause of death are seen to be more pessimistic than by the aggregate mortality. Specifically, the forecast mortality rates by cause of death are slightly higher than the

aggregate mortality rates. This pessimism stems from the independence factor observed in each cause of death, which has a hidden component unique to each cause. Notably, the forecasting period affects the dispersion between cause-specific and aggregate mortality. As shown in Figure 12, for the short-term forecast, the cause of death trend is similar to the aggregate mortality trend. Conversely, the gap between both forecasts becomes more expansive in the mortality forecast 2039. Furthermore, the main cause of death attributes in any age group results in higher mortality forecasts by cause of death compared to aggregate forecasts. The proportion of the cause of death in the respective age groups also influences this outcome. If the cause of death for a certain age group is significant, then the mortality forecast by cause of death shall yield higher values for that age group. Importantly, this result is also aligned with existing literature [10], [16], and [17].

It is also worth noting that the differences between cause-specific and aggregate mortality forecast values are significant at older ages. The forecast trends for cause-specific and aggregate mortality begin to diverge notably in the age groups above 60 years. This divergence may be due to the increased sensitivity of causes of death at older ages, where distinct factors influence the mortality trend. Specifically, the mortality trend becomes more dynamic when reflecting cause-specific mortality at older ages. Generally, this suggests that any proportional changes in causes of death, forecast characteristics, and age groups will lead to discrepancies between cause-specific and aggregate mortality forecasts. However, precise analysis and evidence on this are essential.

The LC model utilised in this analysis may present certain limitations, mainly due to its assumption of linearity in age patterns. This assumption may fail to account for the non-linearities and complex behaviours exhibited by the data. Further refinements are necessary to enhance the reliability of forecasts and provide deeper insights into specific mortality trends. This could involve revisiting and redefining the cause-of-death categories to improve model accuracy. Additionally, exploring extensions of the LC model, such as the Cairns-Blake-Dowd (CBD) model or cohort-based frameworks, may offer a more robust approach to capturing intricate mortality trends. These extensions are better suited to accommodate non-linear patterns and cohort-specific dynamics, potentially addressing the limitations of the standard LC model. Moreover, future research could explore alternative ARIMA specifications for forecasting different causes of death. Since mortality trends may vary significantly across causes, tailoring the ARIMA model parameters to capture the dynamics better could improve cause-specific mortality forecasts' accuracy.

Finally, this study is significant because it highlights the necessity for accurate, cause-specific mortality forecasts to enhance public health strategies and resource allocation. By being aware of these subtle disparities, policymakers and healthcare providers can more effectively target initiatives to lower death rates and better prepare for future healthcare demands. This research can inform targeted public health interventions, healthcare resource allocation, and long-term strategic planning by providing nuanced insights into mortality trends.

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