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Mortality Modelling and Forecasting: An Application of The Lee-Carter Model on The Japanese Data

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Abstract
Accurate mortality modeling and forecasting are essential for understanding population health trends, informing public health policies, and improving demographic projections. This study applies the Lee-Carter (LC) model to Japanese mortality data from 1947 to 2022 to analyze trends and improve predictive accuracy. The dataset, obtained from the Human Mortality Database, is split into training and testing sets (90:10, 80:20, and 70:30) to evaluate model performance. To enhance projection accuracy, the LC model is integrated with the autoregressive integrated moving average (ARIMA) model. The findings reveal a steady decline in mortality rates for both genders, with female mortality following a smoother trend, while male mortality exhibits greater fluctuations. Life expectancy projections indicate a continued upward trend, with female life expectancy consistently surpassing that of males throughout the forecast period (2023–2032). Performance evaluations using Root Mean Square Error (RMSE), Mean Absolute Error (MAE), Mean Absolute Percentage Error (MAPE), and Mean Squared Error (MSE) confirm that larger training datasets improve predictive accuracy, as demonstrated by the superior performance of the 90:10 split. The LC model effectively captures historical mortality trends, though some smoothing effects were observed. The U-shaped mortality pattern —characterized by high infant mortality, low childhood mortality, and increasing mortality with age—aligns with expected demographic trends. Additionally, economic recessions have had a stronger impact on male mortality, particularly due to increased suicide rates linked to job insecurity. Overall, this study demonstrates the LC model's reliability in mortality forecasting, highlighting its potential for guiding public health policies. Future research may explore advanced machine learning techniques to further enhance predictive accuracy.

Keywords*:* ARIMA, Demographic, Lee-Carter model, Mortality, Life expectancy

1. Introduction

Mortality is a key indicator of population well-being and is studied across multiple disciplines, including medicine, demography, public health, and social sciences. Analyzing mortality patterns and trends helps assess public health conditions, evaluate healthcare interventions, and guide policy decisions [1]. Mortality rates offer insights into disease incidence, injury patterns, lifestyle habits, and healthcare accessibility, all of which shape overall population health [2].

Through mortality analysis, researchers can identify health disparities, assess healthcare systems, and develop strategies to enhance quality of life.

Mortality studies serve several crucial purposes. First, they help identify prevalent diseases contributing to significant mortality within a population, enabling medical research and efficient resource allocation in healthcare sectors [3]. Analyzing mortality data allows researchers to track disease dynamics, detect emerging health threats early, and develop preventative measures to reduce premature deaths [4]. Furthermore, mortality trends reveal the effectiveness of healthcare interventions, aiding policymakers in focusing on strategies that yield positive health outcomes [5]. Mortality research also highlights the impact of social determinants such as socioeconomic status, geographic location, and healthcare accessibility on health disparities and life expectancy [6].

One of the earliest approaches to mortality modeling was the Gompertz model, introduced by Benjamin Gompertz in 1825. While historically significant, this model struggles to accurately predict modern mortality trends, particularly among younger populations [7]. In contrast, the Lee-Carter (LC) model incorporates age and time effects, making it more adaptable for forecasting mortality trends [8]. Booth and Tickle [9] further demonstrated that the LC model produces more accurate mortality projections by effectively capturing fluctuations in mortality rates. Although the Gompertz model retains historical relevance, it lacks the predictive power and flexibility of the LC model in contemporary mortality research.

Comparative studies of mortality forecasting techniques have evaluated a range of predictive approaches, including Bayesian methods and deep learning models [9-11]. These studies focus on comparing forecasting methods to determine their accuracy across different demographic contexts [11-12] . Identifying the most reliable forecasting techniques remains a primary goal in mortality research. Mortality forecasting has become increasingly essential in modern demographic studies, providing insights into population health trends, informing social progress, and shaping policy decisions.

The LC model, introduced by Lee and Carter [13], is one of the most widely used mortality forecasting models due to its adaptability and accuracy. It decomposes the age-time mortality rate matrix using principal component analysis, representing it as a bilinear sum of age and period effects. The time component is then projected using time-series models to estimate future mortality trends. Over the years, refinements have improved the LC model's predictive accuracy. For example, Xia [14] reformulated the LC model using a Poisson regression approach to address the assumption of constant error variance. Additionally, multi-factor variations and a generalized LC model incorporating cohort effects have been developed to enhance model fit.

The LC model's popularity stems from its simplicity, interpretability, and reliability. Unlike more complex models that require extensive computations, it remains straightforward to implement while maintaining high forecasting accuracy. The model has been applied across various countries, including Indonesia [15], India [16], Brazil [17], Hungary [18], Thailand [19], and Malaysia [20]. In the United States, Lee and Carter [13] applied the model to forecast national mortality rates. These applications demonstrate its reliability in capturing mortality trends across diverse populations and periods. The LC model remains a preferred choice among demographers and actuaries due to its consistent accuracy [21].

This study analyzes mortality trends in the Japanese population by examining historical data and identifying patterns over time. It applies to the LC model alongside the autoregressive integrated moving average (ARIMA) model to enhance forecasting accuracy by capturing both long-term structural trends and short-term fluctuations. However, the accuracy of the LC model depends significantly on data quality, as poor data selection can result in inaccurate predictions and misinformed policy decisions. To address this, the study evaluates the impact of data selection on forecasting accuracy and assesses the LC model's predictive performance using various statistical metrics. The findings contribute to the advancement of mortality modeling techniques, offering practical insights for demographers, healthcare planners, and policymakers in preparing for future demographic shifts. The structure of this paper is as follows: Section 2 outlines the data and methodology used in the study. Section 3 presents the results and analysis. Finally, Section 4 summarizes key findings and suggests directions for future research.

2. Methodology

For this research, Japan mortality data was obtained from the Human Mortality Database (https://mortality.org/). The dataset includes central mortality rates and mid-year population estimates, categorized by individual ages up to 95+ years, spanning the years 1947 to 2022. In this study, ages above 95 were grouped as 95+ to avoid irregular rates for these ages. To assess model performance, the dataset is split into training and testing sets based on periods using three different ratios: 90:10, 80:20, and 70:30, as shown in Table 1.

Table 1: Training and Testing Data Splits (90:10, 80:20, 70:30)

Ratio	Training years	Testing years
90:10	1947–2014	2015–2022
80:20	1947–2007	2008–2022
70:30	1947–1999	2000–2022

The LC model, introduced in 1992, is expressed as follows:

$$ln\big(m(x,t)\big) = a(x) + b(x)k(t) + \varepsilon(x,t), x = 0, \dots, x_m \tag{1}$$

where $m(x,t)$ is the central mortality rate, calculated by dividing the number of individuals aged x who died in year t by the exposure to death for that age group.

$$\hat{a}(x) = \frac{\sum_{t=1}^{n} ln\,(m(x,t))}{n} \tag{2}$$

$a(x)$ is the average age-specific mortality, $b(x)$ is a deviation in the mortality caused by changes in $k(t)$, $k(t)$ is the mortality index, $\varepsilon(x,t)$ is the residual at age x and time t, and $m(x,t)$ is the age-specific death rate for the x interval and the year t [22]. These variables are independent and identically distributed, with a normal distribution $N(0,\sigma^2)$ with mean 0 and variance σ^2. The parameters $b(x)$ and $k(t)$ are estimated using singular value decomposition (SVD), while $a(x)$ is the average of $\ln(m(x,t))$ across time. The following restrictions were placed to ensure uniqueness of the solution [13]:

$$\sum_{x_0}^{x_m} b(x) = 1 \; and \; \sum_{t_1}^{t_n} k(t) = 0. \tag{3}$$

Applying SVD in the matrix $Z(x,t)$ [23]:

$$Z(x,t) = ln\big(m(x,t)\big) - \hat{a}(x) \tag{4}$$

produces:

$$ULV' = SVD\big(Z(x,t)\big) - L(1)U(x,1)V(t,1) + \cdots + L(X)U(x,X)V(t,X) \tag{5}$$

where L is the singular value, V is the time component, and U is the age component. Estimating $a(x)$, $b(x)$, and $k(t)$ from past age-specific death rates is the first stage in using the LC model to predict mortality. Finding the average of $\ln(m(x,t))$ across time yields estimates of $\hat{a}(x)$. By estimating the first term, the estimates of $\hat{b}(x)$ and $\hat{k}(t)$ may be produced [22], where:

$$\hat{\mathrm{b}}(\mathrm{x}) = \frac{1}{\sum_{\mathrm{x}} \mathrm{u}(\mathrm{x},1)} (\mathrm{u}_1, 1, \mathrm{u}_2, 1, \ldots, \mathrm{u}_\mathrm{x}, 1)^\mathrm{n} \tag{6}$$

$$\hat{\mathrm{k}}(\mathrm{t}) = \sigma_1 \times (\mathrm{v}_1, 1, \mathrm{v}_2, 1, \ldots, \mathrm{v}_\mathrm{t}, 1) \tag{7}$$

After estimating all the parameters, the forecasted and actual death rates are calculated. However, a significant discrepancy often exists between them. Therefore, it is necessary to re-estimate $k(t)$ by satisfying Eq. 2 and to estimate $\hat{b}(x)$ to ensure that the forecasted and actual death rates match [24]. Thus, the parameter estimates satisfy the following condition:

$$\sum_{\mathrm{x}=\mathrm{x}_1}^{\mathrm{x}_\mathrm{m}} \mathrm{D}(\mathrm{x},\mathrm{t}) = \sum_{\mathrm{x}=\mathrm{x}_1}^{\mathrm{x}_\mathrm{m}} E(x,t)\big[exp\,(\hat{\mathrm{a}}(\mathrm{x}) + \hat{\mathrm{b}}(\mathrm{x})\hat{\mathrm{k}}(\mathrm{t}))\big] \tag{8}$$

where $\sum_{x=x_1}^{x_m} \mathrm{D}(x,t)$ is the total number of deaths in year t [24].

To ensure that the predicted number of deaths closely matches the observed number of deaths for a given period, the estimates were adjusted. The ARIMA model, specifically the ARIMA (0,1,0) model initially employed by Lee and Carter [13], is widely used for modeling random walk with drift and forecasting the time-varying index $k(t)$,

$$\hat{k}(t) = \hat{k}(t-1) + \theta + \varepsilon(t) \tag{9}$$
$$\varepsilon_t \sim N(0, \sigma_k^2)$$

where $\varepsilon(t)$ represents normally distributed error terms with a mean of 0 and variance σ_k^2, and θ is the drift parameter [22]. To obtain the predicted values of $m(x,t)$, the projected values of the modified $k(t)$ are substituted into Eq. (1) along with the estimated $a(x)$ and $b(x)$:

$$\widehat{m}(x,n+h) = \widehat{m}(x,n)exp\big\{\hat{b}(x)(\hat{k}(n+h) - \hat{k}(n))\big\} \tag{10}$$
$$h = 1,2,\ldots \quad x = 1,2,\ldots,n$$

where x is the age group, n is the most recent year with available data, and h is the projection horizon.

Life expectancy is calculated by integrating the projected $k(t)$ with the estimated $a(x)$ and $b(x)$ to derive forecasted age-specific mortality rates for future years. It is assumed that the force of mortality $x(t)$ remains constant within each age group. Before computing the average life expectancy, the mortality rate $m(x,t)$ is transformed into the probability of death $q_{x,t}$.

$$q_{x,t} = \frac{2\mathrm{m}(\mathrm{x},\mathrm{t})}{1 + 2\mathrm{m}(\mathrm{x},\mathrm{t})} \tag{11}$$

Life expectancy is then determined using the equation:

$$e_x(t) = \frac{1}{2} + \sum_{n-1}^{\infty} \prod_{x=0}^{n-1} P_{x,k}(t)\,, \tag{12}$$

where $P_{x,k}(t) = \prod_{i=0}^{x-1}[1 - q_{x+i}(t)]$ [25]Click or tap here to enter text..

To evaluate the accuracy of the LC model for mortality forecasts, several statistical measures are commonly used. In this study, RMSE, MAE, MAPE, and MSE were employed as key performance metrics, defined as follows:

$$RMSE = \sqrt{\frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2} \tag{13}$$

$$MAE = \frac{1}{n}\sum_{t=1}^{n}|A_t - F_t| \tag{14}$$

$$MAPE = \frac{100\%}{n}\sum_{t=1}^{n}\left|\frac{A_{t-}F_t}{A_t}\right| \tag{15}$$

$$MSE = \frac{1}{n}\sum_{t=1}^{n}(A_t - F_t)^2 \tag{16}$$

where A_t is the actual value, F_t is the predicted value, and n is the number of observations [26]Click or tap here to enter text..

3. **Results and Discussion**

Figure 4.1 shows the relationship between the logarithm of the death rate and age for Japanese males and females, revealing a similar mortality pattern for both genders. The lines are color-coded using a rainbow gradient, with red representing the earliest year and violet the most recent. Each line represents a specific year, providing a clear visualization of mortality trends over time.

Infant mortality starts high but drops sharply after birth, influenced by socioeconomic conditions and healthcare access [27]. Mortality rates remain low and stable during childhood and early adulthood, reflecting Japan's strong public health policies, disease prevention efforts, and lifestyle interventions [28-29]. From age 40 onward, mortality gradually rises due to age-related health risks and a growing prevalence of lifestyle-related diseases such as cardiovascular conditions and diabetes [28]). After age 60, the increase in mortality becomes steeper, with greater variability among individuals aged 80 and above. Chronic diseases, particularly cancer and cardiovascular illnesses, are the leading causes of death in this age group [30]. These trends highlight improved survival rates over time, demonstrating the impact of healthcare advancements, disease prevention, and lifestyle improvements on Japan's population health.

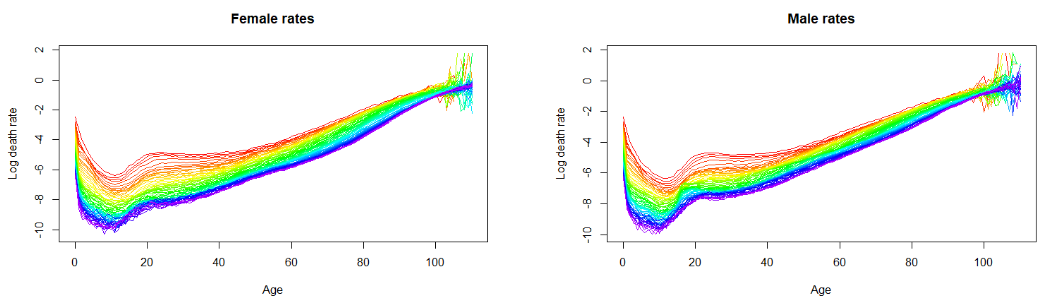

Figure 4.1: Log Death Rates Against Age

Figure 4.2 shows the relationship between log death rates and years for Japanese males and females, showing a consistent decline in mortality over time. The lines follow the same rainbow gradient, with red for the earliest year and violet for the most recent. Each line represents a specific year, providing a clear visualization of mortality trends over time. The most significant decline occurred between 1950 and 1980, slowing in later decades. Male mortality fluctuates more, particularly at older ages, while female mortality follows a smoother and more gradual decline.

Higher log death rates at the top of the graph correspond to older individuals, while lower lines indicate improvements in mortality among younger cohorts. Female mortality remains consistently lower than male mortality, aligning with the well-established trend of higher female life expectancy. Socioeconomic factors contribute to gender differences in mortality. Japan's economic stagnation from the 1990s to the early 2000s led to increased male mortality, particularly due to higher suicide rates linked to job insecurity and financial stress [31]. In contrast, women, despite facing caregiving and work-related stress, benefit from stronger social support networks, which help mitigate some of these risks [32].

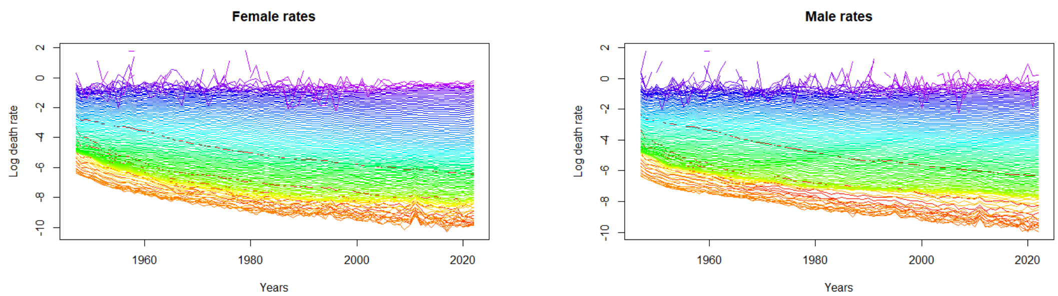

Figure 4.2: Log Death Rates Against Years

Table 4.1: Life Expectancy for the Next 10 Years

Year	2023	2024	2025	2026	2027	2028	2029	2030	2031	2032
Female Life Expectancy	87.68	87.89	88.10	88.30	88.50	88.70	88.90	89.10	89.29	89.48
Male Life Expectancy	81.35	81.56	81.76	81.97	82.17	82.37	82.57	82.76	82.96	83.15

Table 4.1 presents a steady increase in life expectancy for Japanese males and females from 2023 to 2032. Female life expectancy remains consistently higher, reaching 89.48 years in 2032, compared to 83.15 years for males, reflecting the well-established trend of women outliving men. The 6.33-year gap suggests that lifestyle-related diseases, occupational hazards, and stress-related conditions continue to impact male mortality more significantly. While improvements in healthcare, disease prevention, and lifestyle factors contribute to the rising life expectancy for both genders, the slower increase in male longevity highlights the need for targeted health interventions to reduce preventable mortality and promote overall well-being.

Tables 4.2 and 4.3 present the performance metrics of the LC model in forecasting mortality rates for Japanese females and males using different training-testing ratios (90:10, 80:20, and 70:30). The results indicate that the model performs better with a larger training dataset, as seen in the lower RMSE, MAE, MAPE, and MSE values in the 90:10 split for both genders. For Japanese females (Table 4.2), RMSE increases from 0.5208 (90:10) to 0.9432 (70:30), indicating a rise in prediction errors as the training set decreases. Similarly, MAE rises from 0.4188 to 0.7493, MAPE from 0.0567 to 0.1041, and MSE from 0.2712 to 0.8896. This pattern suggests that reducing the training dataset leads to decreased accuracy.

A similar trend is observed for Japanese males (Table 4.3). RMSE rises from 0.2779 (90:10) to 0.4240 (70:30), while MAE increases from 0.1982 to 0.3024. Additionally, MAPE grows from 0.0302 to 0.0476, and MSE from 0.0772 to 0.1798, further confirming that a smaller training set leads to higher errors and reduced predictive reliability. These findings align with existing literature on mortality forecasting, which suggests that larger training datasets improve predictive accuracy by providing more historical patterns for learning [13]. Conversely, smaller training data sets increase the risk of overfitting, which reduces the model's ability to generalize to new data [9].

Table 4.2: Performance Metrics for Japanese Females (90:10, 80:20, 70:30 Splits)

Performance measures	Train-test years of 90:10 ratio	Train-test years of 80:20 ratio	Train-test years of 70:30 ratio
RMSE	0.5208	0.7824	0.9432
MAE	0.4188	0.6354	0.7493
MAPE	0.0567	0.0861	0.1041
MSE	0.2712	0.6121	0.8896

Table 4.3: Performance Metrics for Japanese Males (90:10, 80:20, 70:30 Splits)

Performance measures	Train-test years of 90:10 ratio	Train-test years of 80:20 ratio	Train-test years of 70:30 ratio
RMSE	0.2779	0.3754	0.4240
MAE	0.1982	0.2683	0.3024
MAPE	0.0302	0.0400	0.0476
MSE	0.0772	0.1409	0.1798

In summary, the results indicate that the LC model performs best with larger training datasets, as shown by the higher accuracy of the 90:10 training-test split for both males and females.

4. Conclusion

This study analyzed mortality forecasting using the LC model, demonstrating its robustness and applicability to Japanese male and female mortality data. The LC model remains a benchmark in mortality forecasting, allowing comparisons with newer techniques to assess their strengths and limitations. The results highlight the role of statistical measures, such as RMSE, MAE, MAPE, and MSE, in evaluating forecast accuracy. Among these, MAE is less influenced by outliers compared to RMSE. Mortality trends in Japan show a steady rise in life expectancy, with high infant mortality in early years, stabilization in childhood, and a gradual increase in mortality with age. Female mortality consistently remains lower than male mortality, influenced by socioeconomic conditions, healthcare policies, and lifestyle factors. Economic recessions have also affected male mortality rates more significantly.

The study also examined the impact of different training-to-testing ratios (90:10, 80:20, 70:30) on model performance. The findings show that the LC model achieves higher accuracy with larger training datasets, while reducing training data leads to increased errors. The integration of the ARIMA(0,1,0) model with the LC model effectively captured historical trends and projected future mortality rates, though some smoothing effects were observed. Overall, the results align with the study's objectives, confirming an upward trend in life expectancy and a persistent gender gap in mortality, largely influenced by socioeconomic and health-related factors. The LC model remains a reliable tool for mortality forecasting, but its accuracy depends on the volume of training data. Future research could explore Bayesian methods or deep learning techniques to improve predictive performance, especially when data availability is limited [10] and [12].

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