ANALITIKA:
Journal Of Economics, Management, And Business

Volume 1, Issue 2, 2026, pp. 73-86
ISSN: 3163-4354 (Online); ISSN: 3163-3641 (Print)
DOI: 10.55080/analitika.v1i2.1980

# Comparison of Brass Logit and Kostaki Accuracy in Life Table Reconstruction for Insurance Premiums

**Priscila O.G Limbong [1], Nalar Istiqomah [*)2]**
[1]Trisakti School of Insurance, Jakarta, Indonesia; priscila24limbong04@gmail.com
[2] Trisakti School of Insurance, Jakarta, Indonesia; nalar.istiqomah23@gmail.com
[*)]Corresponding author; E-mail addresses: nalar.istiqomah23@gmail.com

**Article Info**

**Article history:**
Received April 24, 2026
Revised April 29, 2026
Accepted May 06, 2026
Available online November 05, 2026

**Keywords:** Life Table, Brass Logit, Kostaki, Interpolation, Term Life Insurance Premium

**Abstract.** Despite the widespread use of interpolation methods in mortality studies, limited research has conducted a comprehensive comparison of their statistical accuracy and financial implications in the Indonesian context. This study addresses the limited availability of complete mortality data in Indonesia, where mortality information is commonly presented in abridged life tables with five-year age intervals, creating challenges for accurate premium determination. The objective of this research is to compare the performance of the Brass Logit and Kostaki methods in reconstructing complete life tables and to evaluate their impact on term life insurance premium estimation. A quantitative comparative approach is employed using secondary data from the Coale Demeny West Model, Indonesia's life expectancy published by Statistics Indonesia, and the Indonesian Mortality Table IV as the benchmark. The analysis involves model level selection, interpolation, accuracy evaluation using Root Mean Square Error, and application to premium calculations. The results show that the Brass Logit method provides higher statistical accuracy, while the Kostaki method produces premium estimates closer to the benchmark. These findings highlight a trade-off between statistical precision and financial relevance, offering practical guidance for method selection and supporting more robust actuarial decision making in the insurance industry

## Introduction

Population and labor dynamics are strategic issues that are closely related to the national development process. Indonesia is currently facing a major challenge in utilizing the demographic dividend, where the proportion of the productive-age population has reached a significant level. Based on projections by the Ministry of National Development Planning/Bappenas (2023), Indonesia's population is expected to reach approximately 319 million by 2045 (Sagara et al., 2025). This condition reflects the complexity of population-related issues, which require the availability of accurate, comprehensive, and up-to-date demographic data as a foundation for effective and sustainable development policies. In addition to population size and distribution, demographic data also include key dynamics such as births, deaths, and migration, which serve as important references in formulating sustainable public policies.

One of the main components of population dynamics with broad implications for economic development is mortality. Mortality not only reflects the health condition and quality of life of a population but also indicates the effectiveness of the healthcare system and the level of social welfare in a country (Naibaho et al., 2025). From the perspective of contemporary demographic economics, mortality dynamics are viewed as an indicator of human capital quality that significantly influences labor productivity and long-term economic growth. Recent empirical studies show that increases in life expectancy and declines in mortality rates are positively associated with human capital accumulation, labor force participation, and economic growth stability (Naibaho et al., 2025; Resti et al., 2020). In Indonesia, the incomplete epidemiological transition and disparities in access to healthcare services across regions result in variations in mortality patterns that require more detailed analysis.

In demographic and actuarial studies, life tables are fundamental instruments for modeling mortality risk and calculating actuarial values. Indonesia has established the Indonesian Mortality Table (TMI IV) as a national reference; however, in comparative studies and demographic modeling, the use of international standard models such as Coale Demeny remains necessary for analytical and methodological comparison purposes. These models are generally constructed in age intervals, requiring further statistical processes to estimate consistent and applicable single-age mortality probabilities. Therefore, statistical approaches capable of producing smooth and stable mortality structures are essential, particularly in actuarial applications that are sensitive to changes in mortality patterns.

One commonly used approach to construct complete life tables from interval-based data is interpolation. Interpolation methods are widely used to construct complete life tables from abridged data, especially when detailed mortality information is unavailable (Camarda, 2012; Cheng et al., 2022; Dyrting & Taylor, 2024; Rizzi et al., 2015). Mortality data are often reported in grouped age intervals, requiring appropriate methods to estimate single-age mortality rates, including both statistical and machine learning approaches (Nigri et al., 2024; Rizzi et al., 2015). The Brass Logit method is a parametric approach that relies on logit transformation of the survival function to adjust mortality patterns to a standard reference table. Studies have shown that this method produces stable mortality estimates and consistent relationships with the reference population (Sofiyani & Permanasari, 2023). In contrast, the Kostaki method is a nonparametric approach that offers greater flexibility, particularly when mortality distributions across age groups are not proportional. Previous studies indicate that the Kostaki method and its modifications can produce smoother and more realistic estimates of mortality probabilities with high accuracy, making it suitable for actuarial applications such as term life insurance premium calculations (Eldora et al., 2024; Resti et al., 2020). Statistical approaches have been widely applied in mortality modeling to improve estimation accuracy (Brouhns et al., 2002).

In a broader context, various statistical and stochastic approaches have also been developed to model mortality patterns, including the Lee–Carter model and its extensions, which are widely used in demographic and actuarial studies (Booth et al., 2002; Cairns et al., 2006; Li & Lee, 2005; Renshaw & Haberman, 2006). However, these approaches generally require complete mortality data, which are often unavailable in developing countries, thereby highlighting the importance of interpolation-based methods.

Previous studies have compared different mortality modeling approaches to improve estimation accuracy and forecasting performance (Atance et al., 2020; Li & Lee, 2005). Several studies have compared parametric and nonparametric interpolation approaches, showing that different methods may yield varying levels of accuracy and stability in mortality estimation (Atance et al., 2020; Ferenci, 2023). However, most studies tend to apply interpolation methods separately without conducting comprehensive comparative analyses. As a result, differences in parametric and nonparametric assumptions may lead to variations in mortality structures, which can significantly

affect life insurance premium calculations. Furthermore, studies that specifically compare the Brass Logit and Kostaki methods using abridged life tables based on the Coale–Demeny model, particularly in the Indonesian context, remain limited.

Based on these conditions, this study aims to conduct a comparative analysis of the Brass Logit and Kostaki methods in interpolating abridged life tables based on the Coale Demeny model into complete life tables, as well as to evaluate their impact on term life insurance premium calculations.

## Method

This study employs a quantitative approach with a comparative design to examine the differences between the Brass Logit and Kostaki interpolation methods in constructing complete mortality tables and to assess their implications for term life insurance premium calculations. The quantitative approach is applied as the analysis relies on mathematical modeling and numerical computation, while the comparative design enables the evaluation of differences in method performance in terms of accuracy and their impact on premium values. All analytical procedures are conducted within an actuarial framework, based on the principles of actuarial present value and survival probabilities.

The data used in this study are secondary data obtained from official sources and scientific literature. These include the Coale–Demeny West Model life tables as the basis for interpolation, Indonesia's life expectancy published by BPS-Statistics Indonesia for determining the appropriate model level, and the Indonesian Mortality Table IV (TMI IV) as the benchmark. In addition, the BI 7-Day Reverse Repo Rate of 4.75% is applied as the discount factor in actuarial calculations.

### Determination of Coale–Demeny Mortality Table Level

The initial stage of this research is to determine the level of the Coale-Demeny West mortality table that best fits the mortality conditions in Indonesia (Novika & Suryamika, 2024). The Coale-Demeny model consists of several levels, each representing different mortality rates and life expectancies. Therefore, selecting the appropriate level is a crucial step to ensure the underlying mortality structure closely approximates the Indonesian population.

The level determination is performed by comparing the Indonesian Life Expectancy ($e_0$) with the Life Expectancy at each Coale-Demeny table level. The absolute difference between these two values is calculated, and the level with the smallest difference is selected as the most representative. Mathematically, this process is formulated as follows (Coale et al., 1983; Veron et al., 2002):

$$min \mid e_0^{obs} - e_0^{level} \mid$$

where $e_0$ denotes the life expectancy at birth.

### Mortality Table Interpolation Using the Brass Logit Method

The Brass Logit method was originally introduced by Brass (1974) and has been widely applied in mortality estimation and life table construction, particularly when data are incomplete or aggregated (Veron et al., 2002). The Brass Logit method is a parametric interpolation technique used to adjust the mortality pattern of a population to a standard mortality table. This method transforms the survival function into a logit form, allowing the relationship between the observed life table and the standard table to be expressed linearly. This transformation enables adjustments to the shape of the mortality curve while preserving its fundamental characteristics.

The relationship between the interpolated survival probability and the standard survival probability is defined as follows (Ah Khaliludin et al., 2019):

$$logit(1 - l_x) = \alpha + \beta logit(1 - {}^{s}l_x)$$

The logit transformation is defined as:

$$logit(l_x) = ln\left(\frac{l_x}{1 - l_x}\right)$$

where $l_x$ denotes the survival probability at age $x$, $l_x^{(s)}$ represents the survival probability from the standard life table, and $\alpha$ and $\beta$ are parameters estimated through linear regression.

Once the survival probabilities for each single age are obtained, the probability of death is calculated as (Dickson et al., 2019; Veron et al., 2002):

$$q_x = 1 - \frac{l_{x+1}}{l_x}$$

**Mortality Table Interpolation Using the Kostaki Method**

The Kostaki method is based on extensions of classical mortality modeling approaches, providing flexible estimation of age-specific mortality patterns (Kostaki, 1992). The Kostaki method is a non-parametric interpolation method developed to produce more flexible mortality estimates. This method assumes that the survival probability in the interval mortality table is the result of raising the single-age survival probability of a standard table to a specific constant power.

The Kostaki constant is calculated using the equation (Eldora et al., 2024; Resti et al., 2020):

$$K_x^n = \frac{ln\left(1 - {}_nq_x\right)}{\sum_{i=0}^{n-1} ln\left(1 - q_{x+i}^{(S)}\right)}$$

Subsequently, the single-age death probability resulting from the interpolation is obtained through:

$$q'_x = 1 - \left(1 - qx^{(S)}\right)^{K_x^n}$$

Calculations are performed up to the highest age to obtain a complete mortality table from the interpolation.

**Calculation of Annuity Value and Term Life Insurance Value**

After the complete life table is constructed, the value of a temporary life annuity-due is calculated as the basis for premium determination. This annuity represents the present value of periodic premium payments over the coverage period, taking into account the survival probabilities of the insured and the applicable discount factor (Dickson et al., 2019).

$$\ddot{a}_{x:\overline{n}|} = \sum_{k=0}^{n-1} v^k \, {}_kp_x$$

The term life insurance value is calculated as the present value of the death benefit:

$$A^1{}_{x:\overline{n}|} = \sum_{k=0}^{n-1} v^{k+1}\ {}_kp_x\ q_{x+k}$$

**Premium Calculation with the True Fractional Premiums Model**

Premium calculations are conducted using the equivalence principle between the present value of premiums and the present value of benefits. The annual premium is obtained from (Dickson et al., 2019):

$$P_{x:\overline{n}|} = S\frac{A^1{}_{x:\overline{n}|}}{\ddot{a}_{x:\overline{n}|}}$$

For premium payments made more than once a year, the True Fractional Premiums model with fractional annuities is used (Novika & Suryamika, 2024):

$$\ddot{a}^{(m)}_{x:n|} = \ddot{a}_{x:n|} - \frac{m-1}{2m}(1 - v^n\ {}_np^*_x)$$

**Accuracy Evaluation Using Root Mean Square Error (RMSE)**

Accuracy evaluation is performed using Root Mean Square Error (RMSE) to measure the fit of the interpolation results against TMI IV. RMSE is calculated as the square root of the average squared difference between the interpolated death probabilities and the comparison table (Hastie et al., 2009; Prasetyo et al., 2021).

$$\text{RMSE} = \sqrt{\frac{1}{2}\sum_{i=0}^{n}(y_i - \hat{y}_i)^2}$$

A lower RMSE value indicates better model performance, as the predicted values are closer to the observed data. Conversely, a higher RMSE reflects a greater prediction error, suggesting lower model accuracy (Prasetyo et al., 2021). In addition, RMSE is expressed in the same unit as the target variable, which facilitates the interpretation of evaluation results.

**Mortality Curve Analysis**

Mortality curve analysis is conducted by comparing the age-specific death probability patterns derived from the Brass Logit and Kostaki methods with those of TMI IV. The curves are plotted to examine the relationship between age and mortality probability, allowing assessment of the goodness-of-fit, pattern stability, and the rate of increase in mortality at older ages (Atance et al., 2020; Camarda, 2012; Tang et al., 2023). This analysis complements the numerical evaluation and provides a visual assessment of each method's ability to represent the underlying mortality structure (Rizzi et al., 2015).

## Results and Discussion

This study models mortality tables using the Coale–Demeny West Model as the baseline in the form of an abridged life table, which is then expanded into a complete (single-age) life table using two interpolation methods, namely Brass Logit and Kostaki. The analysis is conducted separately for males and females to account for differences in gender-specific mortality patterns. The Indonesian Mortality Table IV (TMI IV) is used as the national benchmark for comparison.

### Determination of the Coale–Demeny Model Level Based on Life Expectancy

The initial stage of the analysis involves determining the Coale–Demeny West model level that best represents Indonesia's mortality conditions. This step is essential, as the selected level serves as the basis for constructing the abridged life table used in the interpolation process. The level is determined using life expectancy at birth ($e_0$), calculated from the standard life table as follows:

$$e_0 = \frac{T_0}{l_0}$$

where $l_0$ represents the initial population (radix), which is set at 100,000 for all levels and both sexes.

The calculation of $e_0$ for levels 21–25 is performed using the R programming language. The Indonesian life expectancy data are processed using the *readxl* package, level identification is conducted using *stringr*, and data manipulation and calculations are carried out using *dplyr*. The results of the life expectancy calculations for each level are presented in Table 1.

**Table 1.** Life Expectancy ($e_0$) by Coale–Demeny Level

| Level | Female $e_0$ | Male $e_0$ |
|---|---|---|
| 21 | 70,0 | 66,03 |
| 22 | 72,5 | 68,57 |
| 23 | 75,0 | 71,20 |
| 24 | 77,5 | 73,91 |
| 25 | 80,0 | 76,65 |

The suitability of each model level is assessed based on the absolute difference between the model life expectancy and Indonesia's observed life expectancy, which is 74.2 for females and 70.3 for males. The comparison results are summarized in Table 2. The smallest difference is obtained at Level 23 for both sexes, indicating that this level provides the closest approximation to Indonesia's mortality conditions.

**Table 2.** Absolute Differences in Life Expectancy

| Level | Female Difference | Male Difference |
|---|---|---|
| 21 | 4,20 | 4,27 |
| 22 | 1,70 | 1,73 |
| 23 | 0,80 | 0,90 |
| 24 | 3,30 | 3,61 |
| 25 | 5,80 | 6,35 |

**Interpolation of Mortality Tables Using the Brass Logit Method**

After selecting the Coale–Demeny West Model at Level 23, the abridged life table is expanded into a complete (single-age) life table using the Brass Logit method. This method calibrates the survival function of the model life table to the standard table (TMI IV) through a logit transformation, with parameters $\alpha$and $\beta$estimated using linear regression in the R software environment.

As an illustration, for females at age 45, the standard survival probability is obtained as $l_{45}^{(s)} = 0.974390396$, with estimated parameters $\alpha = 0.499629$ and $\beta = 1$.

First, the logit transformation of the standard survival probability is computed:

$$\text{logit}(l_{45}^{(s)}) = \ln\left(\frac{l_{45}^{(s)}}{1 - l_{45}^{(s)}}\right) \approx -1.819158$$

Next, the linear transformation is calculated:

$$z_{45} = \alpha + \beta \cdot \text{logit}(l_{45}^{(s)}) = 0.499629 + 1(-1.819158) = -1.319529$$

The interpolated survival probability at age 45 is then obtained using the inverse logit function:

$$l_{45} = \frac{1}{1 + \exp(-z_{45})} \approx 0.933358$$

This value is subsequently converted into radix form (100,000):

$$l_{45} = 0.933358 \times 100{,}000 = 93{,}335.84$$

Finally, the probability of death at age 45 is calculated as:

$$q_{45} = 1 - \frac{l_{46}}{l_{45}} \approx 0.005094$$

The complete interpolation results of mortality probabilities $q_x$using the Brass Logit method are presented in Table 3.

**Table 3.** Interpolation Results of Mortality Probabilities Using the Brass Logit Method

| Age (x) | Female | Male | Age (x) | Female | Male |
|---|---|---|---|---|---|
| 0 | 0.006443 | 0.012352 | 51 | 0.009076 | 0.014086 |
| 1 | 0.001044 | 0.001312 | 52 | 0.009947 | 0.015351 |
| 2 | 0.000794 | 0.001043 | 53 | 0.010862 | 0.016715 |
| ... | ... | ... | ... | ... | ... |
| 49 | 0.007530 | 0.011773 | 99 | 0.257801 | 0.327953 |
| 50 | 0.008279 | 0.012926 | 100 | 1.000000 | 1.000000 |

**Interpolation of Mortality Tables Using the Kostaki Method**

The abridged life table of the Coale–Demeny West Model at Level 23 is transformed into a complete (single-age) life table using the Kostaki method. This procedure begins by constructing

interval death probabilities ${}_nq_x$, which are then calibrated to the standard mortality table (TMI IV) through a proportional adjustment constant $K_x^n$, resulting in a smoother and more consistent series of single-age death probabilities $q'_x$. All computations are implemented using the R programming language.

As an illustration, for males at age 45, the standard survival probability is $l_{45}^{(s)} = 96{,}270.85061$, with the corresponding death probability $q_{45}^{(s)} \approx 0.00302$.

First, the interval death probability is determined. For $x = 45$, the abridged interval is $[45,50)$, so $n = 5$, and:

$$ {}_5q_{45} = \frac{l_{45} - l_{50}}{l_{45}} $$

Next, interpolation is performed using a six-point Lagrange polynomial. However, since $x = 45$is a knot point (the starting point of the interval), the Lagrange interpolation satisfies:

$L_i(45) = 1$ for $x_i = 45, L_i(45) = 0$ for other nodes

Thus, the interpolated value simplifies to:

$$ q_{45} = {}_5q_{45} $$

indicating that the interpolation at this knot point returns the original interval value.

The adjustment constant is then computed as:

$$ K_x^n = \frac{\ln(1 - {}_nq_x)}{\sum_{i=0}^{n-1} \ln(1 - q_{x+i}^{(s)})} $$

For $x = 45$ and $n = 5$, the calculation yields $K_{45}^5 \approx 1.064$.

Finally, the single-age death probability is obtained using:

$$ q'_x = 1 - (1 - q_x^{(s)})^{K_x^n} $$

Thus, for age 45:

$q'_{45} \approx 0.003214632$

The complete interpolation results of mortality probabilities $q_x$using the Kostaki method are presented in Table 4.

**Table 4.** Interpolation Results of Mortality Probabilities Using the Kostaki Method

| Age (x) | Female | Male | Age (x) | Female | Male |
|---|---|---|---|---|---|
| 0 | 0.01530 | 0.02162 | 50 | 0.00381 | 0.00562 |
| 1 | 0.00086 | 0.00117 | 51 | 0.00418 | 0.00616 |
| 2 | 0.00065 | 0.00092 | 52 | 0.00459 | 0.00674 |
| ... | ... | ... | ... | ... | ... |
| 48 | 0.00323 | 0.00445 | 98 | 0.43361 | 0.45314 |
| 49 | 0.00354 | 0.00491 | 99 | 0.45816 | 0.47937 |

**Premium Calculation Using Interpolated Mortality Tables**

Premium calculations are based on the value of a temporary life annuity-due derived from the interpolated mortality tables using the Brass Logit and Kostaki methods. Data processing is conducted using the R programming language by extracting $l_x$ values to compute survival probabilities.

Given an interest rate of $i = 4.75\%$, the discount factor is $v = 0.95464$. For a male insured aged 45 with a 15-year term, the survival probability is calculated as:

$$ {}_{15}p_{45} = \frac{l_{60}}{l_{45}} $$

The annuity values are then computed for different payment frequencies: annual, semiannual ($m = 2$), quarterly ($m = 4$), and monthly ($m = 12$).

**Table 5.** Annuity Values for Males (Age 45)

| *Brass Logit* | | | | |
|---|---|---|---|---|
| x | Annual | Semiannual | Quarterly | Monthly |
| 45 | 10.2803 | 10.1288 | 10.0530 | 10.0025 |
| *Kostaki* | | | | |
| x | Annual | Semiannual | Quarterly | Monthly |
| 45 | 10.7054 | 10.5668 | 10.4975 | 10.4513 |

**Table 6.** Annuity Values for Females (Age 45)

| *Brass Logit* | | | | |
|---|---|---|---|---|
| x | Annual | Semiannual | Quarterly | Monthly |
| 45 | 10.5421 | 10.3986 | 10.3269 | 10.2791 |
| *Kostaki* | | | | |
| x | Annual | Semiannual | Quarterly | Monthly |
| 45 | 10.8115 | 10.6771 | 10.6099 | 10.5652 |

As shown in Tables 5 and 6, the annuity values at age 45 calculated using the Kostaki method are consistently higher than those obtained using the Brass Logit method across all payment frequencies and for both genders. For males, the annual annuity value is 10.71 under Kostaki compared to 10.28 under Brass Logit, while for females the corresponding values are 10.81 and 10.54, respectively. This difference indicates that the mortality table derived from the Kostaki method produces higher survival probabilities, which in turn increases the annuity values.

**Term Life Insurance Premium Calculation (15-Year)**

Premiums are calculated for a 15-year term life insurance product under three benefit scenarios: IDR 300,000,000; IDR 500,000,000; and IDR 1,000,000,000. The calculations are performed for a male insured aged 45, with payment frequencies of annual, semiannual, quarterly, and monthly, based on the interpolated mortality tables derived from the Brass Logit and Kostaki methods.

Using the equivalence principle, the annual premium is determined as:

$$P = \frac{S \cdot A^{1}_{x:\bar{n}}}{\ddot{a}_{x:\bar{n}}}$$

As an illustration, for a benefit of IDR 300,000,000, the premiums obtained using the Brass Logit method are IDR 4,084,861.15 (annual), IDR 2,072,987.59 (semiannual), IDR 1,044,305.77 (quarterly), and IDR 349,859.83 (monthly). In contrast, the Kostaki method yields lower premiums of IDR 1,936,776.59 (annual), IDR 981,093.95 (semiannual), IDR 493,786.31 (quarterly), and IDR 165,323.24 (monthly).

The complete comparison of net premiums for different benefit levels is presented in Table 7 for males and Table 8 for females. As shown in Table 7, premiums for a 45-year-old male increase proportionally with the benefit amount across all methods. For a benefit of IDR 300,000,000 with annual payments, the premium under TMI IV is IDR 1,657,042.94, compared to IDR 1,936,776.60 using the Kostaki method and IDR 4,084,861.15 using the Brass Logit method. This pattern remains consistent for higher benefit levels and across all payment frequencies, where the Brass Logit method consistently produces the highest premiums, while the Kostaki method yields values closer to the TMI IV benchmark.

A similar pattern is observed for females, as shown in Table 8. For a benefit of IDR 300,000,000 with annual payments, the premium under TMI IV is IDR 1,024,282.39, compared to IDR 1,308,103.37 (Kostaki) and IDR 2,724,043.73 (Brass Logit). Across all benefit levels and payment frequencies, the Brass Logit method produces the highest premiums, whereas the Kostaki method consistently provides estimates closer to the benchmark.

These findings indicate that differences in mortality interpolation methods significantly affect premium values. The Brass Logit method tends to produce higher mortality estimates at certain ages, leading to higher premium values, whereas the Kostaki method generates mortality patterns that are more consistent with TMI IV, resulting in more realistic premium estimates. This highlights the importance of selecting an appropriate interpolation method, as it has direct implications for actuarial pricing and financial decision making in the insurance industry.

**Table 7.** Net Premium Comparison for Males (Age 45)

| Payment Type | IDR 300,000,000 | IDR 500,000,000 | IDR 1,000,000,000 |
|---|---|---|---|
| Brass Logit | | | |
| Monthly | 349,859.84 | 583,099.73 | 1,166,199.46 |
| Semiannual | 2,072,987.59 | 3,454,979.32 | 6,909,958.64 |
| Annual | 4,084,861.16 | 6,808,101.93 | 13,616,203.87 |
| Quarterly | 1,044,305.78 | 1,740,509.63 | 3,481,019.26 |
| Kostaki | | | |
| Monthly | 165,323.25 | 275,538.75 | 551,077.50 |
| Semiannual | 981,093.95 | 1,635,156.59 | 3,270,313.17 |
| Annual | 1,936,776.60 | 3,227,960.99 | 6,455,921.99 |
| Quarterly | 493,786.32 | 822,977.19 | 1,645,954.38 |
| TMIV | | | |
| Monthly | 141,383.29 | 235,638.82 | 471,277.64 |
| Semiannual | 839,193.82 | 1,398,656.37 | 2,797,312.73 |
| Annual | 1,657,042.94 | 2,761,738.23 | 5,523,476.47 |
| Quarterly | 422,316.88 | 703,861.47 | 1,407,722.95 |

**Table 8.** Net Premium Comparison for Females (Age 45)

| Payment Type | IDR 300,000,000 | IDR 500,000,000 | IDR 1,000,000,000 |
|---|---|---|---|
| Brass Logit | | | |
| Monthly | 232.811,20 | 388.018,67 | 776.037,33 |
| Semiannual | 1.380.809,93 | 2.301.349,88 | 4.602.699,76 |
| Annual | 2.724.043,73 | 4.540.072,88 | 9.080.145,76 |
| Quarterly | 695.199,84 | 1.158.666,40 | 2.317.332,80 |
| Kostaki | | | |
| Monthly | 111.549,96 | 185.916,59 | 371.833,19 |
| Semiannual | 662.281,60 | 1.103.802,66 | 2.207.605,32 |
| Annual | 1.308.103,37 | 2.180.172,29 | 4.360.344,58 |
| Quarterly | 333.237,35 | 555.395,59 | 1.110.791,18 |
| TMIV | | | |
| Monthly | 87.308,07 | 145.513,45 | 291.026,90 |
| Semiannual | 518.461,28 | 864.102,14 | 1.728.204,28 |
| Annual | 1.024.282,39 | 1.707.137,32 | 3.414.274,64 |
| Quarterly | 260.840,09 | 434.733,49 | 869.466,97 |

### Accuracy Evaluation Using Root Mean Square Error (RMSE)

The accuracy of the interpolation methods is evaluated using the Root Mean Square Error (RMSE), which is defined as:

$$\text{RMSE} = \sqrt{\frac{1}{2}\sum_{i=0}^{n}(y_i - \hat{y}_i)^2}$$

The RMSE is calculated for both the mortality probability ($q_x$) and the number of survivors ($l_x$) over the age range of 0–99 years by comparing the interpolated results with the standard mortality table (TMI IV). In addition, RMSE is also used to measure the deviation between the Brass Logit and Kostaki methods, providing an indicator of the average estimation error between the two approaches.

The results of the RMSE calculations for each comparison are presented in Table 9.

**Table 9.** Accuracy Evaluation of Interpolation Methods (RMSE)

| Gender | Brass Logit vs TMI IV | Kostaki vs TMI IV | Brass Logit vs Kostaki |
|---|---|---|---|
| Female | 0.1248 | 0.4309 | 0.3405 |
| Male | 0.1216 | 0.3378 | 0.2571 |

The results indicate that, for females, the RMSE relative to TMI IV is 0.1248 for the Brass Logit method and 0.4309 for the Kostaki method. For males, the corresponding values are 0.1216 (Brass Logit) and 0.3378 (Kostaki), while the RMSE between the two methods is 0.3405 for females and 0.2571 for males.

As shown in Table 9, the Brass Logit method consistently produces lower RMSE values for both genders, indicating a closer fit to the TMI IV benchmark and lower estimation error compared to the Kostaki method. This suggests that, from a statistical perspective, the Brass Logit method provides more accurate mortality estimates, although, as shown in the premium analysis, this does not necessarily translate into more realistic premium values.

### Mortality Curve Analysis

Mortality interpolation curves are constructed using the R programming language by comparing the complete life tables obtained from the Brass Logit and Kostaki methods with the standard mortality table (TMI IV). The data are aligned over the age range of 0–99 years and visualized as curves of mortality probability ($q_x$) and the number of survivors ($l_x$) for each method. This visualization aims to assess the goodness-of-fit of the interpolated mortality patterns relative to the standard pattern across all age groups.

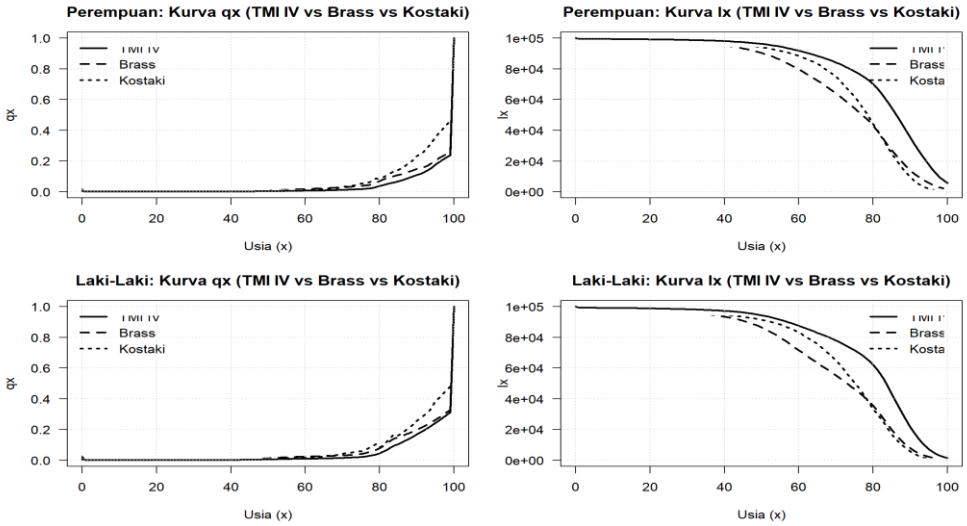



**Image 1.** Mortality Interpolation Curves

As shown in Image 1, the interpolation curve produced by the Brass Logit method more closely follows the pattern of TMI IV compared to the Kostaki method, for both females and males. The differences are most pronounced at older ages, where the Kostaki method tends to produce higher mortality probabilities ($q_x$), resulting in a more rapid decline in the number of survivors ($l_x$) compared to the standard curve. In contrast, the Brass Logit curve more consistently aligns with the TMI IV pattern across most age groups.

These visual findings are consistent with the RMSE results, indicating that the Brass Logit method exhibits lower deviation from the benchmark compared to the Kostaki method. This suggests that the Brass Logit method provides a better statistical fit to the observed mortality structure. Furthermore, this result aligns with previous studies highlighting the sensitivity of mortality models to methodological assumptions and their impact on actuarial outcomes (Atance et al., 2020; Booth et al., 2002; Cairns et al., 2006).

## Conclusion

This study demonstrates that the Brass Logit and Kostaki methods produce different outcomes in reconstructing complete mortality tables and estimating term life insurance premiums. While the Brass Logit method provides higher statistical accuracy by generating mortality patterns that more closely align with the TMI IV benchmark, the Kostaki method yields premium estimates that are more consistent with benchmark-based values. This finding highlights a trade-off between statistical accuracy and financial applicability, indicating that the choice of interpolation method should be aligned with the intended actuarial objective. Future research is recommended to explore sensitivity analysis on key parameters and to extend the model toward gross premium calculations for more practical applications in the insurance industry.

## Bibliography


Ah Khaliludin, N. I., Mohd Khalid, Z., & Abd. Rahman, H. (2019). On Estimate of Malaysian Mortality Rates Using Interpolation Methods. MATEMATIKA, 177–186. https://doi.org/10.11113/matematika.v35.n2.1169

Atance, D., Debón, A., & Navarro, E. (2020). A Comparison of Forecasting Mortality Models Using Resampling Methods. Mathematics, 8(9), 1550. https://doi.org/10.3390/math8091550

Booth, H., Maindonald, J., & Smith, L. (2002). Applying Lee-Carter under conditions of variable mortality decline. Population Studies, 56(3), 325–336. https://doi.org/10.1080/00324720215935

Brouhns, N., Denuit, M., & Vermunt, J. K. (2002). A Poisson log-bilinear regression approach to the construction of projected lifetables. Insurance: Mathematics and Economics, 31(3), 373–393. https://doi.org/10.1016/S0167-6687(02)00185-3

Cairns, A. J. G., Blake, D., & Dowd, K. (2006). A Two-Factor Model for Stochastic Mortality with Parameter Uncertainty: Theory and Calibration. Journal of Risk and Insurance, 73(4), 687–718. https://doi.org/10.1111/j.1539-6975.2006.00195.x

Camarda, C. G. (2012). MortalitySmooth : An R Package for Smoothing Poisson Counts with P-Splines. Journal of Statistical Software, 50(1). https://doi.org/10.18637/jss.v050.i01

Cheng, Z., Si, W., Xu, Z., & Xiang, K. (2022). Prediction of China's Population Mortality under Limited Data. International Journal of Environmental Research and Public Health, 19(19), 12371. https://doi.org/10.3390/ijerph191912371

Coale, A. J., Demeny, P., & Vaughan, B. (1983). Regional Model Life Tables and Stable Populations (Vol. 2). Elsevier. https://doi.org/10.1016/C2013-0-07295-7

Dickson, D. C. M., Hardy, M. R., & Waters, H. R. (2019). Actuarial Mathematics for Life Contingent Risks. In Annals of Actuarial Science (Vol. 8, Number 2). Cambridge University Press. https://doi.org/10.1017/S1748499514000177

Dyrting, S., & Taylor, A. (2024). Estimating age-specific mortality using calibrated splines. Population Studies, 78(3), 429–446. https://doi.org/10.1080/00324728.2023.2228297

Eldora, F., Azmi, K., Meva, L., Gultom, T., Manullang, S., & Farhana, N. A. (2024). Peningkatan Akurasi Estimasi Probabilitas Kematian Menggunakan Metode Interpolasi Modifikasi Kostaki Dengan Lagrange 6 Titik Pada Tabel Mortalitas Indonesia IV 2019. INNOVATIVE: Journal Of Social Science Research, 4, 961–970.

Ferenci, T. (2023). Comparing methods to predict baseline mortality for excess mortality calculations. BMC Medical Research Methodology, 23(1), 239. https://doi.org/10.1186/s12874-023-02061-w

Hastie, T., Tibshirani, R., & Friedman, J. (2009). The elements of statistical learning (2nd ed.) (2nd ed.). Springer.

Kostaki, A. (1992). A nine-parameter version of the Heligman-Pollard formula. Mathematical Population Studies, 3(4), 277–288. https://doi.org/10.1080/08898489209525346

Li, N., & Lee, R. (2005). Coherent mortality forecasts for a group of populations: An extension of the lee-carter method. Demography, 42(3), 575–594. https://doi.org/10.1353/dem.2005.0021

Naibaho, A. R. O., Alnaya, D., Siregar, F. A., & Purba, B. (2025). Kajian Teoritis Mengenai Morbiditas dan Mortalitas dalam Perspektif Ekonomi Demografi. RIGGS: Journal of Artificial Intelligence and Digital Business, 4(2), 3541–3546. https://doi.org/10.31004/riggs.v4i2.1071

Nigri, A., Levantesi, S., & Scognamiglio, S. (2024). Disaggregating Death Rates of Age-Groups Using Deep Learning Algorithms. Journal of Official Statistics, 40(2), 262–282. https://doi.org/10.1177/0282423X241240739

Novika, F., & Suryamika, P. E. (2024). Rancang produk asuransi jiwa berjangka dengan metode Kostaki melalui model True Fractional Premiums. PYTHAGORAS: JURNAL PROGRAM STUDI PENDIDIKAN MATEMATIKA, 13(2), 146–156. https://doi.org/10.33373/pyth.v13i2.6653

Prasetyo, V. R., Lazuardi, H., Mulyono, A. A., & Lauw, C. (2021). Penerapan Aplikasi RapidMiner Untuk Prediksi Nilai Tukar Rupiah Terhadap US Dollar Dengan Metode Linear Regression. Jurnal Nasional Teknologi Dan Sistem Informasi, 7(1), 8–17. https://doi.org/10.25077/teknosi.v7i1.2021.8-17

Renshaw, A. E., & Haberman, S. (2006). A cohort-based extension to the Lee–Carter model for mortality reduction factors. Insurance: Mathematics and Economics, 38(3), 556–570. https://doi.org/10.1016/j.insmatheco.2005.12.001

Resti, Y., Putra, A. E., & Zayanti, D. A. (2020). Metode Interpolasi Modifikasi Kostaki dalam Menentukan Peluang Meninggal untuk Premi Asuransi Jiwa Berjangka. Jurnal Penelitian Sains, 22(3), 119. https://doi.org/10.56064/jps.v22i3.558

Rizzi, S., Gampe, J., & Eilers, P. H. C. (2015). Efficient Estimation of Smooth Distributions From Coarsely Grouped Data. American Journal of Epidemiology, 182(2), 138–147. https://doi.org/10.1093/aje/kwv020

Sagara, R., Setiawan, A. H., Almuzafir, & Purnawan, E. (2025). Dinamika Kependudukan dan Ketenagakerjaan: Tantangan dan Kebijakan Berkelanjutan untuk Indonesia. Jurnal Alwatzikhoebillah : Kajian Islam, Pendidikan, Ekonomi, Humaniora, 11(1), 317–329. https://doi.org/10.37567/alwatzikhoebillah.v11i1.3629

Sofiyani, S., & Permanasari, Y. (2023). Penerapan Metode Cubic Spline Interpolation untuk Menentukan Peluang Kematian pada Tabel Mortalita. Jurnal Riset Matematika, 29–36. https://doi.org/10.29313/jrm.v3i1.1735

Tang, S., Li, J., & Tickle, L. (2023). A Hermite spline approach for modelling population mortality. Annals of Actuarial Science, 17(2), 243–284. https://doi.org/10.1017/S1748499522000173

Veron, J., Preston, S. H., Heuveline, P., & Guillot, M. (2002). Demography, Measuring and Modeling Population Processes. Population (French Edition), 57(3), 591. https://doi.org/10.2307/1535065