African Journal of Education, Science and Technology (AJEST) Vol 7 No.4 (Published May 2024)
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Constructing Malawian Ordinary Actuarial Tables: Reflection of the COVID-19 Era

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Abstract

An actuarial life table, often known as a mortality table, offers data on the probability or mortality rate within a given population at various ages during a certain period of time. These data are crucial for studying patterns of mortality, forecasting population growth, calculating life expectancy, and pinpointing the main causes of high mortality rates in a population. The lack of mortality tables in Malawi's insurance market is a significant problem for insurance providers. Therefore, the objective of this study is to construct ordinary life tables specifically for Malawi, covering the period from 2016 to 2022. In this study, the raw death rates are smoothed using the Whittaker-Henderson method before being predicted for a five-year period using the logistic regression model. The Malawian ordinary life table was created to show how likely it is that an individual will die increases with age. Additionally, it has been noted that males have a higher mortality rate than females, and further research has revealed that pandemics have an impact on raising mortality rate.

Keywords: actuarial life table, Whittaker-Henderson, forecast, logistic regression model, pandemics

INTRODUCTION

Mortality tables, or actuarial life tables, display death probabilities in defined populations, aiding insurers in claim payouts (Ahmeti, 2013). Businesses are advised to use mortality tables specific to their assured lives for accurate estimations (Rutishauser, 1973). These tables, stemming from John Graunt and Edmond Halley's concept, form the foundational tool for insurance calculations globally (Hustead, 1988). Over time, tailored tables like CSG 1960 for group life insurance and CSO 1941 for individual annuities emerged (Rutishauser, 1973). Abridged and complete life tables, categorized by age intervals, are vital in various sectors (Betts, 2003). Cohort life tables, tracking mortality over time, offer long-term insights (Betts, 2003).

The probability of death, key in life table computations, influences various parameters (Ramadhan, 2022). Graduation methods refine mortality rates, enhancing accuracy (Papaioannou & Sachlas, 2004). Techniques like Gompertz and Whittaker-Henderson smoothing optimize mortality data (Papaioannou & Sachlas, 2004; Jahra, 2019). Logistic regression models forecast death rates effectively (Dokumentov, Hyndman, & Tickle, 2019). For developing nations like Malawi, selecting mortality tables akin to their economic and social context is crucial (Beliu, 2020). Zimbabwe's mortality rates serve as a reference for neighboring countries like Malawi (Beliu, 2020; Nundwe, 2019). Closing gaps in mortality data aids in establishing standard tables for accurate insurance pricing (Nundwe, 2019).

MATERIALS AND METHODS

Data sources and study Description

This study analyzed data from two Malawian life insurance companies, gathering qualitative and quantitative information on individual assured lives from 2016 to 2022. Information on age, gender, and insurance status was collected, including categories such as dead, active, relinquished, or matured policies. Various types of life insurance plans were examined, categorized as savings or risk policies. Mortality rates were calculated for each age group, allowing for comparisons before and after the COVID-19 pandemic and by gender. Predictions for mortality rates over a 5-year period starting in 2022 were also made based on the collected data.

Data Management and Analysis

Any inconsistencies and missing variables were reviewed in Microsoft Excel first to make sure the data was dependable and accurate before being used. One person was removed from the data since it was expected that a policyholder with similar gender, birthdate, and death date would own numerous policies. Additionally, data processing, model fitting, life table construction, and mortality rate predictions were all done using the statistical analysis program R. R was also used for exploratory data analysis, which includes data visualization and analysis of death rate trends.

Calculating Age-Specific Mortality Rates

The mortality rate within particular age groups in a population is referred to as the age-specific mortality rate. It is computed by dividing the total population or the total number of people exposed to the risk of that age group by the number of deaths that occur in that age group. To create life tables, a variety of techniques are available. The choice of the fundamental parameter that is used to calculate the other parameters is where the differences between the tables are most noticeable. According to the presumption that 18 is the minimum age required by law in Malawi for the purchase of a life insurance product, that age was initially chosen for this study. Additionally, how the company determines the initial age is a factor in how premiums are priced for life insurance policies using mortality rates.

Different states may have the policy of a person who has a life insurance product. Active, mature, dead, reinstated, surrendered, or withdrawn are some of these statuses. To ascertain the number of deaths at each specific age and the number of people exposed to risk at that age, the status of the policyholder was used in this study.

The number of surviving lives at age x is reduced by the total of number of withdrawals, surrenders, maturity denoted as w_x and the number of deaths, d_x, of the previous age:

$$l_x = l_{x-1} - d_{x-1} - w_{x-1}$$

where w_x represents the sum of number of withdrawals, surrenders, policies that matured and any reasons other than death on that specified age. This implies that an individual who withdrawals the policy is only exposed to risk from the exact age x to the date of withdrawal.

Therefore, the total number of those exposed to risk at a particular age is denoted as E_x such that the exposure calculated from aggregate data is referred to as grouped or census exposure method:

$$E_x = a_x + d_x$$

where a_x is the number of active members at age x (Chanco, 2016)

The total of those who were still alive at that age and those who were not is the number of people who were exposed to risk. This is true because in the individual life insurance industry, the number of people who canceled their policies would normally be at increased mortality risk for a period of time longer than six months. The assumption is made that people who lapsed or withdrew their policies were not exposed to the risk of dying, which is the event of interest in this study, because these events frequently occur on premium due dates, whether at the end of the policy month, quarter, semi-annually, or annually. The total number of individuals exposed to risk is therefore the total number of members at the start of age x, less the withdrawals, surrenders and mature policies over age x (David B. *et al*, 2023).

The formula for calculating the mortality rate is therefore adjusted to incorporate the reduced number of those exposed to the risk of dying due to the withdrawals. Further, the mortality rates calculated in this study are age specific death rates which is the number of deaths that occurred within the specific age divided by the size of that age, hence the number of those exposed to risk in that particular age; $a_x=d_x/E_x$

The general relationship of the sum of probabilities is $p_x+q_x=1$. Similarly, the probability of survival of an individual aged x was calculated by $p_x=1-q_x=1$ instead of $p_x=l_x+(1/l_x)$. For each year x of the life of an individual from the examined population, the functions that are determined for a life table.

Graduating Mortality Rates

The Whittaker-Henderson approach, which regulates the smoothness of the estimated mortality rates by a tuning parameter, spar, was used to get smoothed mortality rates in order to obtain mortality rates that are more accurate and less volatile. The smoothing parameter was changed to balance the trade-off between smoothing the mortality rates by minimizing the penalty term while fitting the crude mortality rates by minimizing the sum of squared residuals. When spar is set at a low value, the Whittaker-Henderson graduation technique produces a smooth curve; however, when spar is set at a higher value, the curve more closely resembles the reported crude mortality rates. In addition, regardless of the Whittaker-Henderson being the widely adopted graduation method used in actuarial practice (Biessy, 2023), it was preferred in this study due to its ability to balance the trade-off between accurately capturing the underlying mortality trend while minimizing fluctuations and noise present in the raw data of the assured lives Malawian mortality rates. Therefore, this study incorporated the trial and error method by trying different values of the spar and observing the results.

Whittaker-Henderson Method

The Gaussian weighting scheme was used to define the weight matrix which applies the Gaussian distribution to determine the weight based on the distance between mortality rates for instance from age 18 to age 19:

$$w(i,j) = \exp(-\lambda * (i-j)^2)$$

where: w(i,j) is the weight assigned to crude mortality rates position and $(i-j)^2$ is the squared difference between indices of mortality rates.

The smoothing parameter, λ , controls the degree of smoothness in the smooth rates to be obtained and is therefore referred to as the penalty term. As stressed by (Chanco, 2016), various settings for the Whittaker-Henderson graduation formula's parameters, which correspond to the smoothness and fitness to estimate the graduated mortality rates, should be investigated. Similar to that, several values were also explored in this study to assess the smoothed mortality rates; smaller values of lambda provide smoother mortality rates as opposed to bigger values of lambda, which allow for more variance and fit the smoothed rates closely to the observed rates.

The smoothed mortality rates in Whittaker-Henderson method were calculated as below:

$$smoothed\ mortality\ rates = \frac{[^P(weight * crudemortality\ rates]}{[^P weight]}$$

The Whittaker-Henderson minimize the function:

$$Minimise: \sum_{i=1}^{n}[w_i(v_i - u_i)]^2 + \lambda \sum_{i=1}^{n-1}[\Delta u_i]^2$$

where: v_i represents crude mortality rates at each age. w_i represents the non-negative weights assigned to each data point. u_i represents the estimated smoothed rates at each x_i

A smoothed rate is iterated over a number of times in the Whittaker-Henderson method to improve the smoothed mortality rates. In this work, the smoothed mortality rates underwent ten iterations to further improve them. Additionally, while lambda affects the level of smoothness, the number of iterations ensure convergence and enhance the accuracy of the smoothing process.

The optimization problem was solved in R software using to estimate the smooth mortality rates. To fully analyze the smooth rates, the control parameter, λ, was adjusted by trial and error method emphasized by (Cairns, 2002) for the need to experiment with different values of the smoothing parameter to obtain optimal results.

Test of goodness of fit

The observed data were compared to the expected data using the goodness of fit test to see if they match. The probable error test, Chi-square test, serial correlation, absolute deviation test, standardized deviation test, cumulative deviation test, and the Steven's or grouping of signs test are some of the goodness of fit techniques used when creating actuarial tables (Tables, 2022).

Signs Test

In this study, the p-values from testing the goodness of fit of the Whittaker-Henderson method, which was used to grade the crude mortality rates, were compared to assess the accuracy and dependability of smoothed mortality rates. The Signs test was appropriate for this investigation because, in circumstances where the data are not normally distributed, as in our case with death rates, it is particularly noteworthy. On the basis of various values of λ, the test statistic for each outcome of smooth mortality rates was calculated. To achieve this, fewer counts of both positive and negative discrepancies between the smoothed mortality rates and the crude mortality rates were chosen.

Forecasting

The crude death rate is calculated by dividing the number of registered deaths in a year by the mid-year population for the same year.A logistic regression model was fitted to the annual death rates from 2016 to 2022 whereby the estimates of the coefficients of the predictor variables were processed in R software. The model was then applied to new data to forecast the probability of mortality. However, the logistic regression is expressed as:

$$\log\left(\frac{p}{1-p}\right) = \beta_0 + \beta_2 x_2 + \cdots + \beta_p x_p$$

Where: log(p/(1-p)) is the log odds (logit) of the probability of the binary outcome. p is the probability of the binary outcome. β_0 is the intercept or constant term while, β_1, β_2,..., β_p are the coefficients or weights associated with the predictor variables $x_1, x_2, \ldots, x_p$.

RESULTS AND DISCUSSION

With the p-values obtained in Table 1, resulting from the assessment of the goodness of fit for the Whittaker-Henderson method using various λ values, insights into the statistical significance of the model's performance were drawn across different smoothing parameter settings.

Table 1. Assessment of the goodness of fit for the Whittaker-Henderson method

Model	spar(λ)	p-value
Whittaker Henderson	0.09	0.0442626
	0.5	0.7981526
	0.98	0.6089207

In figure 1, we see that λ=0.09 has balanced well between the fitness and smoothness of data.

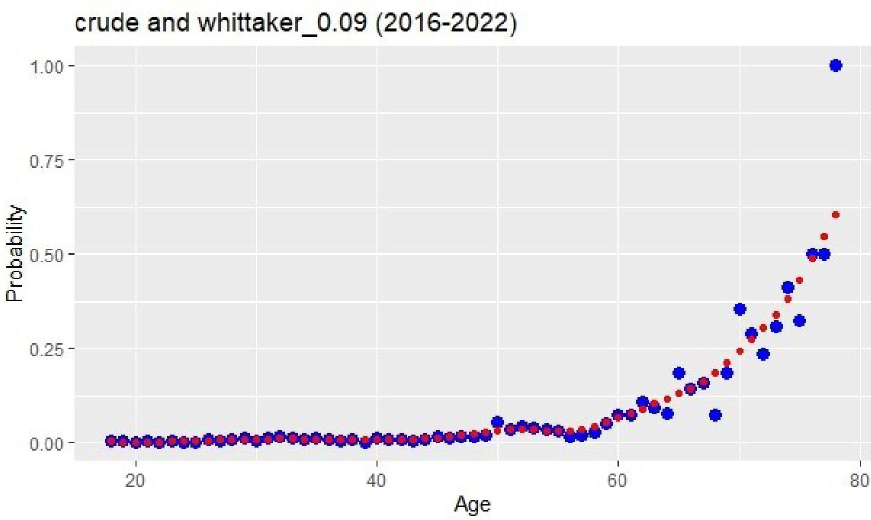

Figure 1. Smooth mortality rates (Whittaker-Henderson 0.09)

Figure 2, the Whittaker-henderson 0.5 has not balanced well between fitness and smoothness of the data as compared to both λ=0.09 and 0.98

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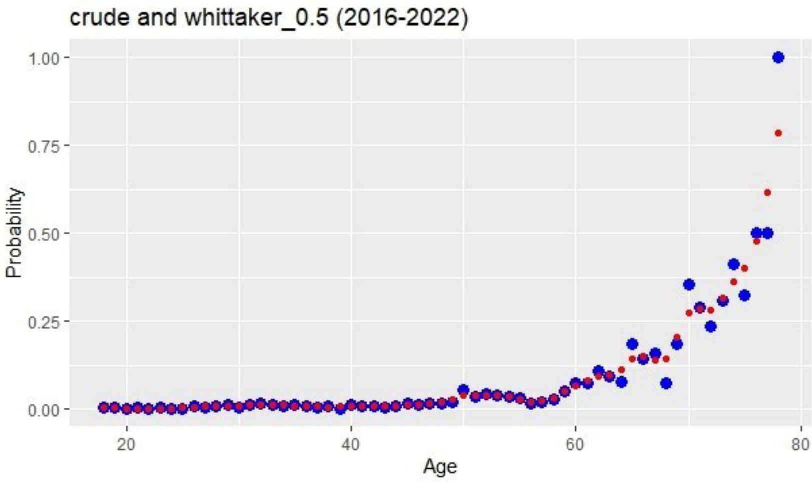

Figure 2. Smooth mortality rates (Whittaker-Henderson 0.5)

In Figure 3, the Whittaker-henderson 0.98 has not balanced well between fitness and smoothness of the data as compared to both λ=0.09

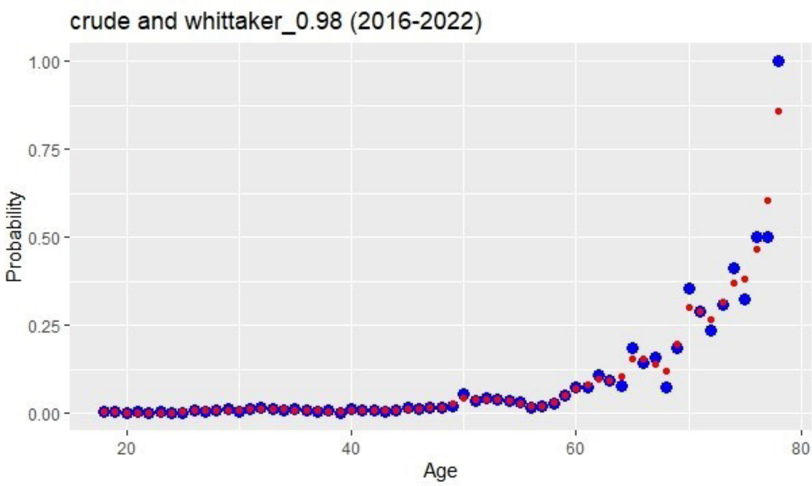

Figure 3. Smooth mortality rates (Whittaker-Henderson 0.98)

The visualization of how different values of λ impacted the smoothness of mortality rates in the Whittaker-Henderson method has been shown in the Figure 1, 2 and 3 above.

With the p-values obtained below resulting from the assessment of the goodness of fit for the Whittaker-Henderson method using various λ values, insights into the statistical significance of the model's performance were drawn across different smoothing parameter settings;

Malawian Ordinary Life Tables

Based on age-specific mortality rates for those aged 18 to 78, period life tables for the years 2016 to 2022 were created by dividing the number of fatalities by the number of people exposed to risk at each specified age. To obtain estimates of the underlying rates that are more accurate and less variable across all ages, the crude mortality rates were graduated using the Whittaker-Henderson method with $\lambda = 0.09$. The Whittaker-Henderson method with $\lambda = 0.09$ was opted because it had the least p-value and balanced well between the fitness and smoothness of the data. The table 3 of Appendix A is the Malawian Ordinary Life

Figure 4, has been constructed based on the smoothed probabilities of dying.

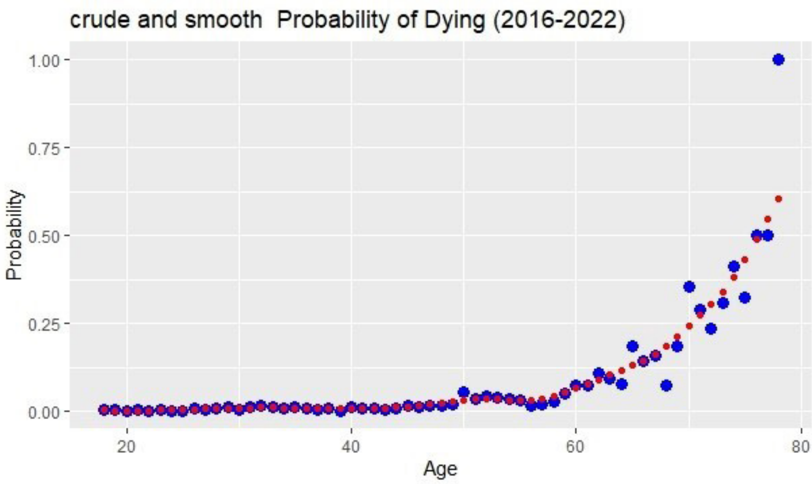

Figure 4: Malawian age specific mortality rates (2016-2022)

According to Kleinbaum, D. G. and Klein, (2012) the likelihood of a person living over the limit (inf) is zero. Because survival is a non-increasing function, it is therefore assumed that an individual will eventually pass away as time passes. The Malawian ordinary life table established has clearly showed that as age increases, the probability of a person dying likewise increases due to the real life related aspects of survival probabilities. According to ((UNESCAP), 2022), the average mortality pattern over age-specific death rates is J-shaped because the mortality rate rises as age rises. As a result, the Malawian life table supplied shows a clear trend showing that as people age, their life expectancy decreases.

Mortality Rates on Males and Female

The analysis of the effect of gender on death rates was another goal of this work. The gender-based age-specific death rates are shown for men and women in table 2 of Appendix A. It has been shown that when a person's age increases, both males and females are more likely to pass away thanks to research that takes into account both factors' effects on mortality rates. The death rate for males is higher than for females, it has been observed. Ratele, (2008) presents and examines when and how South African males start to disappear from the population and suggests that the numerical differences between the sexes evident in the population figures are related to gender practices. According to Ratele, (2008), explores when and how South African men begin to withdraw from the population and proposes that gender practices are responsible for the numerical disparities between the sexes that are apparent in population data. Further research revealed that adult males die in greater numbers than adult females as a result of dangerous masculine behaviors.

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Similar to this, job hazards and healthcare utilization where males prefer to seek medical attention less frequently than females are contributing contributors to the reported gender inequalities in mortality rates. Figure 5 illustrates this graphically.

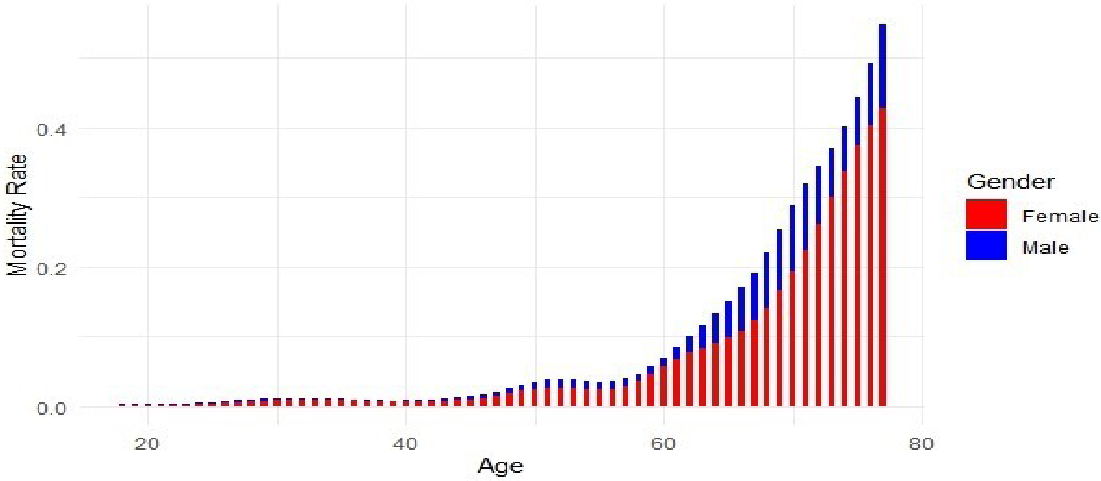

Figure 5. Comparison between males and females mortality rates

Analysis on Pre and Post Covid-19

Computing annual probabilities of death made it easier to compare mortality statistics before and after the COVID-19 era began. Pre-pandemic phase was investigated to be between 2016 and 2019; post-pandemic phase was examined to be between 2020 and 2022, taking into account the impact of COVID-19 on Malawi. This distinction has been made in light of the finding that most COVID-19 cases started to appear in Malawi and other African nations in the year 2020. The death rates in Malawi from 2016 through 2022 are shown in Table 2.

Table 2. Annual death rate in Malawi.

Year	Deaths	Population	Death-rate
2016	259	10149	0.02552
2017	195	9448	0.020639
2018	185	14186	0.013041
2019	123	13596	0.009047
2020	275	12343	0.02228
2021	333	13406	0.02484
2022	257	16119	0.015944

In Figure 6 the mortality trend is visually represented for comprehensive analysis of death rates from 2016 to 2022.

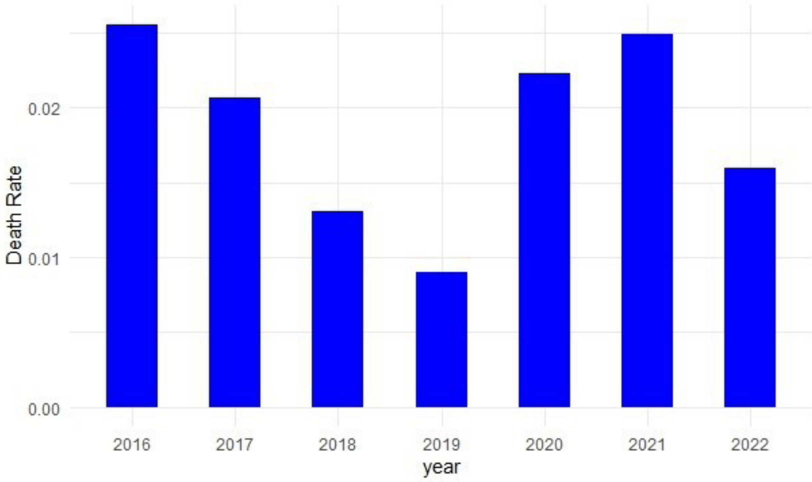

Figure 6. Comparison of the covid-19 era

The data shows that death rates fluctuate, and that they will start to decline before 2020, which will signal an improvement in health and living conditions. After that, there is a brief rise in mortality rates during the pandemic, particularly in the years 2020 and 2021. According to another analysis, people buy more life insurance due to human behavior since they are more likely to be exposed to dangers like pandemics. The desire to shift the risk to the insurance firms led to a rise in the demand for insurance among the public during the epidemic, as shown by Qian, (2021). Similarly, in the assured death rates of Malawian context, the proportion of the number of deaths and those exposed became low hence a subsequent decrease in 2022 since the demand for insurance becomes high resulting in more number of individuals exposed to risk.

Forecasted of Annual Death Rates (2023-2027)

The prior analysis revealed that starting in 2022, death rates started to drop. In order to anticipate the yearly death rates starting in 2023 over the next five years, an analysis was done. Table 3 displays the projected death rates.

Table 3. Forecasted death rates

Year	Death – Probability
2023	0.017223
2024	0.016862
2025	0.016509
2026	0.016163
2027	0.015825

The projected death probability point to a constant and gradual decline in mortality rates over the following five years. The improvement in living standards and breakthroughs in healthcare are thought to be indicators of this declining tendency. But it's possible to expect that mortality rates would go up again in the event of a potential future pandemic.

CONCLUSION AND RECOMMENDATIONS

Conclusion

There is a noticeable rise in death rates as people age. This implies that the likelihood of dying increases as people age. Because of age-related illnesses like hypertension, there is a strong link between mortality and age across many populations. Additionally, gender has a substantial impact on death rates. Risky activities and workplace dangers among men are some of the elements that contribute to this aspect and lead to increased mortality rates.

It has also been determined that annual death rates decline over time. The mortality rates do, however, start to climb again in response to events like pandemics. Additionally, the projected trend in mortality rates from 2023 to 2027 suggests that policyholders would experience a decreasing risk of passing away over the following five years beginning in 2022. This could aid life insurance companies in managing risks and streamlining their pricing tactics.

Recommendations

This study suggests that insurance companies should launch products that offer coverage specifically for pandemics or other infectious diseases on the insurance market. This is due to the possibility that higher mortality rates during pandemics could undermine the life insurance firms' capacity to maintain their financial stability. The Malawian health industry and life insurance businesses ought to work closely together. This is so that they can obtain health ministry records in cases where the policyholder's death hasn't been disclosed to the insurers. As a result, a precise assessment and premium calculation can be made using an analysis of the mortality rates among policyholders.

Further research should look into the relationship between mortality rates and mental health. Predicting mortality rates while taking things like pandemics and other new diseases into consideration. Examining the variations in death rates between younger policyholder groups and older age groups.

ACKNOWLEDGEMENT

Valuable data for this research was provided by Old Mutual Life Assurance and Vanguard Life Assurance companies.

REFERENCES

(UNESCAP), U. N. E. and S. C. for A. and the P. (2022). Age-specific Mortality in Fiji: First Workshop on the Use of Administrative Data for Mortality Statistics.

Ahmeti, U. (2013). The importance and characteristics of life insurance. Research Journal of Finance and Accounting, 4(19)., 188–189.

Beliu, E. *et al*. (2020). A stochastic mortality model for the albanian life insurance companies. Knowledge-International Journal, 43(3), 473–476.

Betts, K. (2003). Review of don rowland, demographic methods and concepts. People and Place, 11(3), 69.

Biessy, G. (2023). Revisiting whittaker-henderson smoothing. ArXiv Preprint ArXiv:2306.06932.

Cairns, A. J. (2002). A comparative study of various graduation methods. North American Actuarial Journal, 6(4), 38–56.

Chanco, M. E. (2016). Mortality rates estimation using whittaker-henderson graduation technique. Social Security System, Quezon City, Philippines, Journal of the Mathematical Society of the Philippines, 39, 7–16.

David B. Atkinson, Fsa, m. and John k. Mcgarry, Asa, P. (2023). SOA Experience Study Tool. https://Www.Soa.Org/Resources/TablesCalcs-Tools/Experience-Study-Tool/.

Dokumentov, A., Hyndman, R. J., and Tickle, L. (2019). Bivariate smoothing of mortality surfaces with cohort and period ridges. Stat, 7(1):E199. E199 Sta4.199.

Hustead, E. C. (1988). The history of actuarial mortality tables in the united states. Journal of Insurance Medicine, 20(4), 12–16.

Jahra, F. T. (2019). Essays on the whittaker-henderson method of graduation.

Kleinbaum, D. G. and Klein, M. (2012). Survival Analysis: A Self-Learning Text, Third Edition. Springer-Verlag New York, New York.

Nundwe, L. (2019). Overview of the insurance industry in malawi. Financial Service Agency.

Papaioannou, T. and Sachlas, A. (2004). Graduation of mortality rates revisited. University Of.

Qian, X. (2021). The impact of covid-19 pandemic on insurance demand: the case of china. The European Journal of Health Economics, 22, 1017–1024.

Ramadhan, M. H. (2022). Constructing an abridged life table based on estimator of the probability of death using maximum likelihood estimation. In Proceedings of the 2nd National Conference on Mathematics Education 2021 (NaCoME 2021). Atlantis Press., 147–150.

Ratele, K. (2008). Masculinity and male mortality in south africa. African Safety Promotion, 6(2), 19–41.

Rutishauser, H. (1973). Mortality tables. South African Medical Journal, 47(20), 855–858.

Tables, Z. M. (2022). Development of zimbabwe mortality tables. Https://Ipec.Co.Zw/ Findata/Vfm-Admin/Vfm-Downloader.Php?

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