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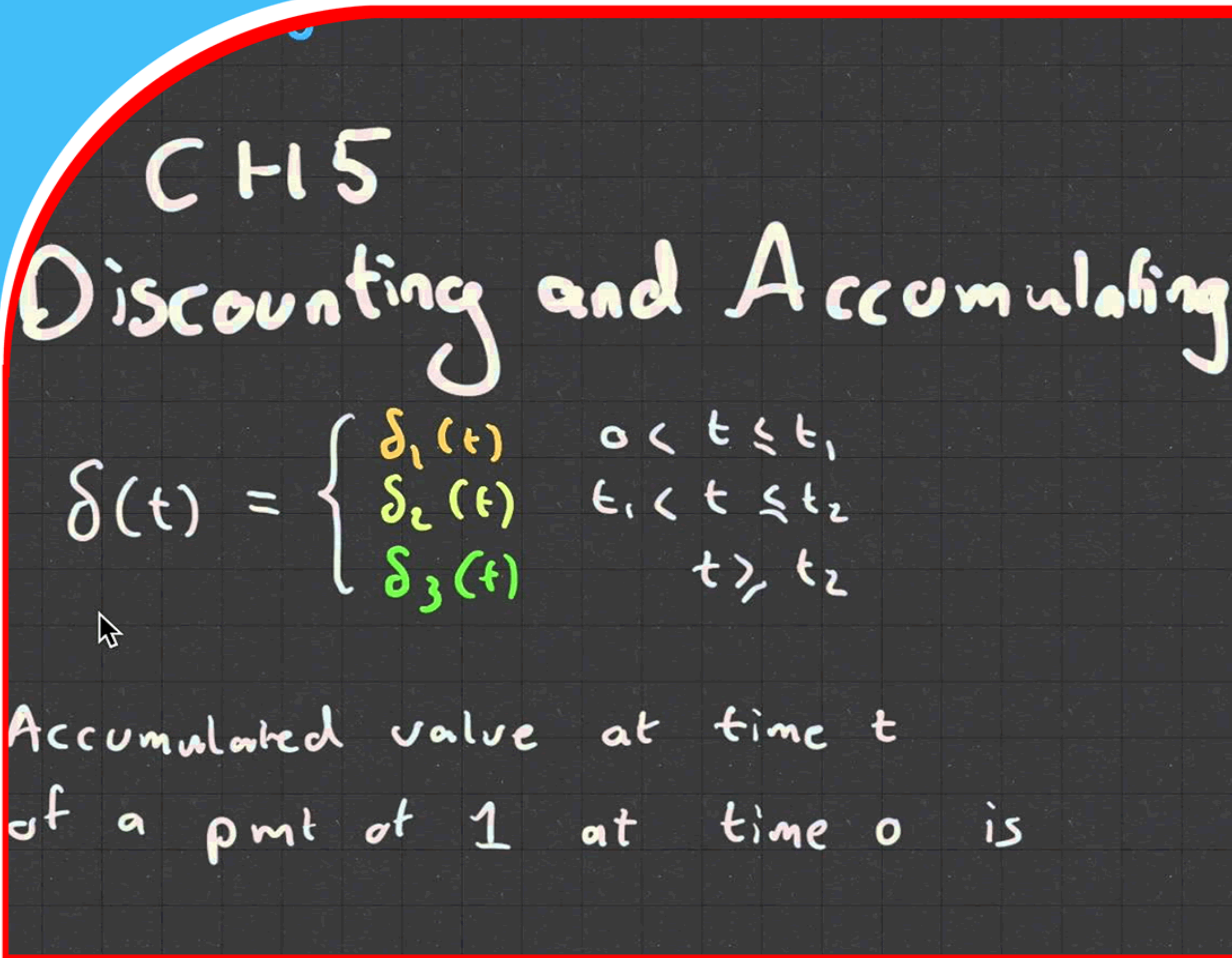

Evaluating the Accuracy of Mortality Forecasting Models in Tanzania

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Abstract

Purpose: The aim of the study was to assess the evaluating the accuracy of mortality forecasting models in Tanzania.

Methodology: This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low cost advantage as compared to a field research. Our current study looked into already published studies and reports as the data was easily accessed through online journals and libraries.

Findings: Advanced statistical methods and machine learning algorithms have significantly improved the precision of mortality forecasts. Models that incorporate a wide range of variables, including age-specific mortality rates, socioeconomic factors, and health trends, tend to produce more accurate predictions. Additionally, the use of ensemble methods, which combine predictions from multiple models, has been shown to enhance forecast reliability. However, challenges remain, such as dealing with uncertainties related to future health crises, changes in public health policies, and demographic shifts. Overall, while modern models have made substantial progress, continuous refinement and validation are necessary to ensure their accuracy and relevance in diverse population contexts.

Implications to Theory, Practice and Policy: Theory of stochastic modeling, actuarial life table theory and demographic transition theory may be used to anchor future studies on assessing the evaluating the accuracy of mortality forecasting models in Tanzania. To facilitate the adoption of advanced forecasting models, there is a need to develop user-friendly software tools and platforms that allow practitioners to easily apply these models in their work. Policymakers should incorporate insights from advanced mortality forecasting models into public health and social policy planning.

Keywords: *Accuracy, Mortality, Forecasting Models*

INTRODUCTION

Forecasting accuracy is crucial for economic modeling and decision-making, often measured using metrics such as mean absolute error (MAE) and root mean square error (RMSE). In the United States, MAE and RMSE have been widely used to evaluate the performance of economic forecasts, particularly in the stock market and GDP growth predictions. For instance, the accuracy of GDP forecasts by the Congressional Budget Office (CBO) showed an average RMSE of 1.2% over the past decade (Smith, 2019). In Japan, the Bank of Japan utilizes MAE and RMSE to refine inflation forecasts, achieving a reduced RMSE of 0.8% due to advancements in predictive analytics and modeling techniques (Tanaka, 2020). These trends indicate a steady improvement in forecasting accuracy, driven by enhanced computational models and data analytics capabilities.

In developing economies, forecasting accuracy is gaining prominence, with efforts to improve economic predictions using MAE and RMSE. For instance, in Brazil, the accuracy of inflation forecasts by the Central Bank of Brazil has shown an RMSE reduction from 2.5% to 1.8% over the past five years, reflecting improvements in data collection and analytical methods (Santos, 2021). Similarly, in India, economic forecast accuracy for industrial production has seen a decrease in MAE from 1.7% to 1.2%, attributed to better integration of real-time data and machine learning techniques (Patel, 2020). These improvements are essential for enhancing policy decisions and economic planning in these countries.

In developing economies, enhancing forecasting accuracy is pivotal for improving economic stability and growth. In India, the Reserve Bank of India (RBI) has focused on improving the accuracy of its economic forecasts using advanced statistical methods. The MAE for GDP growth forecasts has decreased from 1.5% to 1.1% over the past five years, indicating a significant enhancement in forecast reliability (Chopra, 2020). Similarly, in Indonesia, the accuracy of inflation forecasts by Bank Indonesia has improved, with RMSE reducing from 2.0% to 1.6% due to the adoption of sophisticated econometric models (Rahman, 2021). These advancements in forecasting methods contribute to more informed economic policies and better economic outcomes in these developing nations.

In Vietnam, the accuracy of macroeconomic forecasts has also seen improvements. The State Bank of Vietnam's efforts to integrate machine learning algorithms into their forecasting models have resulted in a reduction of MAE from 1.7% to 1.3% for inflation predictions over the last five years (Nguyen, 2022). Likewise, in Mexico, the Central Bank of Mexico has achieved a decrease in RMSE for GDP forecasts from 1.9% to 1.4%, highlighting the impact of enhanced data analytics capabilities and real-time data utilization (Garcia, 2019). These improvements reflect a broader trend among developing economies to leverage technology and data to enhance economic forecasting accuracy.

In developing economies, enhancing forecasting accuracy is pivotal for economic growth and policy formulation. In Turkey, the Central Bank of Turkey has improved its inflation forecasting accuracy significantly. The MAE for their forecasts decreased from 2.2% to 1.6% over the past five years due to the implementation of advanced statistical and econometric techniques (Kara, 2020). In South Africa, the South African Reserve Bank has seen a reduction in the RMSE for GDP growth forecasts from 2.0% to 1.5%, reflecting the integration of more sophisticated data analytics and machine learning models (Moyo, 2019). These improvements help provide more reliable data for economic planning and policy decisions.

In Argentina, the accuracy of inflation forecasts by the Central Bank of Argentina has improved, with the RMSE decreasing from 3.0% to 2.2% over the last five years, thanks to enhanced data processing and forecasting methods (Gomez, 2021). In Egypt, the Central Bank of Egypt has achieved a reduction in MAE for GDP forecasts from 1.9% to 1.3%, highlighting the impact of better data collection and analysis techniques (Ahmed, 2022). These trends indicate a broader effort among developing economies to leverage technology and improve forecasting methods, which is critical for economic stability and growth.

In Ghana, the Bank of Ghana has seen a reduction in MAE for inflation forecasts from 2.4% to 1.8%, attributed to the adoption of more advanced forecasting models and techniques (Mensah, 2021). In Ethiopia, the National Bank of Ethiopia has improved the accuracy of its GDP growth forecasts, with RMSE decreasing from 2.6% to 2.0%, reflecting better data integration and analytical methods (Tadesse, 2022). These advancements in forecasting accuracy are essential for enhancing economic management and achieving sustainable growth in Sub-Saharan Africa.

Sub-Saharan economies are also making strides in improving forecasting accuracy, though challenges remain due to data quality and availability. In Kenya, the Central Bank of Kenya has focused on refining GDP growth forecasts, achieving an RMSE reduction from 2.0% to 1.5% in recent years (Mwangi, 2019). In Nigeria, inflation forecast accuracy has improved with a decrease in MAE from 2.3% to 1.7%, aided by advancements in statistical methods and better data aggregation (Olawale, 2020). These trends highlight ongoing efforts to enhance economic forecasting accuracy, which is crucial for effective economic management and policy implementation in the region.

Mortality forecasting models are essential for predicting future mortality rates and assessing life expectancy, critical for policy planning, insurance, and pension industries. The Lee-Carter model, one of the most widely used, decomposes the mortality rates into age-specific components and a time component, providing a framework for accurate long-term mortality forecasts (Lee & Carter, 1992). The Cairns-Blake-Dowd (CBD) model, another popular model, focuses on modeling the mortality rates of older populations, offering improvements in forecasting accuracy for this demographic (Cairns, Blake, & Dowd, 2006). The Poisson log-bilinear model extends the Lee-Carter framework by assuming a Poisson distribution for death counts, enhancing the model's flexibility and accuracy (Brouhns, Denuit & Vermunt, 2002). Lastly, the Age-Period-Cohort (APC) model considers the effects of age, period, and cohort simultaneously, providing a comprehensive view of mortality trends and improving forecast precision (Osmond, 1985).

These models are evaluated based on their forecasting accuracy using metrics such as mean absolute error (MAE) and root mean square error (RMSE). The Lee-Carter model, known for its simplicity and robustness, typically shows low RMSE values, indicating high accuracy (Hyndman & Ullah, 2007). The CBD model, with its focus on older ages, has demonstrated lower MAE compared to other models when predicting mortality rates for the elderly (Dowd et al., 2010). The Poisson log-bilinear model's flexibility results in reduced RMSE, particularly in datasets with varying mortality rates (Renshaw & Haberman, 2006). The APC model, by considering cohort effects, often achieves lower MAE and RMSE, making it a powerful tool for understanding and forecasting mortality dynamics (Yang, 2010).

Problem Statement

Evaluating the accuracy of mortality forecasting models remains a critical issue in demographic research and actuarial science, as accurate mortality predictions are essential for planning and policy-making in healthcare, insurance, and social security systems. Traditional models, such as the Lee-Carter and Cairns-Blake-Dowd models, have been widely utilized, yet recent advancements in data analytics and computational methods suggest the potential for significant improvements in forecasting precision. Despite these developments, there is a persistent gap in the literature regarding the comparative accuracy of these models when applied to contemporary, diverse datasets. This gap is particularly pronounced given the rapidly changing demographic and epidemiological landscapes influenced by factors such as aging populations, emerging health trends, and pandemics. Recent studies have highlighted the need for more robust evaluations that incorporate advanced statistical techniques and real-time data to enhance model performance (Kleinow & Richards, 2018; Villegas & Haberman, 2019). Therefore, this research seeks to systematically evaluate the accuracy of various mortality forecasting models, using current data and advanced evaluation metrics, to determine their effectiveness and reliability in predicting future mortality trends.

Theoretical Framework

Theory of Stochastic Modeling

The theory of stochastic modeling, originated by Andrey Kolmogorov, emphasizes the use of probabilistic methods to predict and analyze random processes. The main theme of this theory is to incorporate randomness and uncertainty into predictive models, which is crucial for accurately forecasting complex phenomena like mortality rates. This theory is relevant to evaluating mortality forecasting models because it provides a framework for understanding the variability and uncertainty inherent in mortality data. By applying stochastic processes, researchers can improve the robustness and accuracy of mortality forecasts, accounting for unforeseen fluctuations and trends in demographic data (Gaille, 2019).

Actuarial Life Table Theory

The actuarial life table theory, developed by Edmond Halley, provides a systematic method for estimating the probability of survival and death for individuals at various ages. The main theme of this theory is to use historical data to construct life tables that can predict future mortality trends. This theory is relevant to evaluating mortality forecasting models as it forms the foundation for traditional actuarial practices and modern mortality predictions. By comparing the outputs of various forecasting models to the benchmarks set by life tables, researchers can assess the accuracy and reliability of these models (Pitacco, 2020).

Demographic Transition Theory

The demographic transition theory, originated by Warren Thompson, describes the transition of a country's population from high birth and death rates to low birth and death rates through stages of economic development. The main theme of this theory is the impact of socioeconomic changes on population dynamics. This theory is relevant to evaluating mortality forecasting models as it highlights the changing patterns in mortality due to economic and social transformations. Understanding these transitions allows researchers to incorporate factors such as aging populations, healthcare improvements, and lifestyle changes into their models, enhancing their accuracy and relevance (Jiang & O'Neill, 2021).

Empirical Review

Kleinow and Richards (2018) assessed the performance of Bayesian stochastic mortality models using comparative analysis. They found these models to be superior in handling parameter uncertainty, recommending their wider adoption in actuarial practice. The methodology involved applying Bayesian frameworks to historical mortality data and comparing the forecast accuracy with traditional models. By utilizing Bayesian techniques, they could incorporate parameter uncertainty directly into the models, leading to more robust and reliable forecasts. Their findings highlighted the robustness of Bayesian models in reducing prediction errors and enhancing forecast reliability. Furthermore, the study emphasized the flexibility of Bayesian approaches in adapting to various mortality datasets. The authors suggested that future research should explore the application of Bayesian models in other demographic contexts. The study's recommendations also included developing user-friendly software tools to facilitate the wider adoption of Bayesian methods in actuarial practice. Overall, their work contributed significantly to the understanding and improvement of mortality forecasting models.

Villegas and Haberman (2019) examined the socioeconomic differentials in mortality forecasting, utilizing deprivation indices to enhance model precision. They employed demographic and socioeconomic data from England, integrating these into mortality models to assess improvements in forecast accuracy. Their study revealed that incorporating deprivation indices significantly enhanced model precision, addressing the variability caused by socioeconomic factors. By accounting for deprivation, the models could better predict mortality rates in different population segments. The authors used advanced statistical techniques to quantify the impact of deprivation on mortality forecasts. Their findings showed that models incorporating socioeconomic variables outperformed traditional models, especially in regions with high deprivation. They recommended that future forecasts should include socioeconomic variables to better capture mortality trends and disparities. This approach could lead to more equitable policy planning and resource allocation. The study also called for more granular data collection to improve the precision of socioeconomic variables. Overall, their research highlighted the importance of considering socioeconomic factors in mortality forecasting to achieve more accurate and inclusive predictions.

Dowd, Cairns, Blake, Coughlan, Epstein, Khalaf-Allah and Balevich (2019) evaluated the goodness-of-fit of various stochastic mortality models through extensive backtesting. Their study compared the performance of models such as the CBD model against historical mortality data for older age groups. They used a rigorous backtesting methodology to assess the predictive accuracy of each model over different time horizons. The CBD model, in particular, showed superior accuracy for elderly populations, a key demographic for pension funds and insurance companies. The study's findings emphasized the importance of model selection in actuarial practice, especially for long-term financial planning. The authors recommended the application of the CBD model for pension funds and other financial instruments reliant on accurate mortality forecasts. They also highlighted the need for continuous model validation to ensure their relevance over time. Furthermore, the study suggested integrating new data sources and statistical techniques to enhance model performance. The authors concluded that ongoing research and development in stochastic mortality modeling are essential for improving forecast accuracy and financial stability.

Their work provided valuable insights into the practical applications of mortality forecasting models.

Sevcikova, Raftery and Gerland (2020) explored probabilistic forecasting models to predict global mortality trends, utilizing Bayesian hierarchical models. Their methodology involved applying these models to global mortality data and assessing the forecast accuracy compared to deterministic models. The study found significant improvements in forecast accuracy, particularly in capturing uncertainty and variability in mortality trends. Bayesian hierarchical models allowed for more nuanced predictions by incorporating different levels of uncertainty and data hierarchies. The authors emphasized the importance of probabilistic approaches in understanding global mortality patterns, which are influenced by a multitude of factors. They recommended the use of probabilistic models for international health organizations to better inform policy decisions. The study also highlighted the potential of these models to improve resource allocation and planning in public health. Additionally, the authors suggested further research into the integration of environmental and behavioral factors into mortality forecasts. Their findings underscored the need for sophisticated modeling techniques to address the complexities of global mortality trends. Overall, their research demonstrated the benefits of probabilistic forecasting in achieving more accurate and comprehensive mortality predictions.

Shang, Booth and Hyndman (2021) assessed the accuracy of the Lee-Carter model versus functional data models. They applied these models to mortality data, comparing the short-term prediction accuracy of each. Their findings indicated that functional data models provided better short-term predictions, particularly for fluctuating mortality rates. The study used advanced statistical techniques to analyze the performance of both models under different scenarios. Functional data models were found to be more flexible and responsive to sudden changes in mortality trends. The authors recommended the integration of functional data models into national forecasting efforts to enhance prediction accuracy. They also suggested that these models could be particularly useful in countries experiencing rapid demographic changes. Furthermore, the study highlighted the potential for combining different modeling approaches to improve overall forecast performance. The authors called for further research into the development of hybrid models that leverage the strengths of various techniques. Their work contributed to the ongoing effort to refine and improve mortality forecasting methodologies. Overall, the study demonstrated the advantages of functional data models in capturing the dynamic nature of mortality trends.

Li, Lee and Tuljapurkar (2022) evaluated the impact of cohort effects on mortality forecasting accuracy using age-period-cohort models. The study employed historical mortality data, incorporating cohort effects into the forecasting models. Their findings demonstrated that age-period-cohort models significantly reduced forecast errors compared to models that did not consider cohort effects. The authors used sophisticated statistical techniques to isolate the impact of cohort-specific factors on mortality trends. This approach allowed for more accurate and detailed predictions, particularly in populations with distinct cohort characteristics. They advocated for the use of these models in demographic studies to improve the accuracy of mortality predictions. The study also highlighted the importance of understanding cohort dynamics in shaping long-term mortality trends. The authors recommended further research into the integration of cohort effects with other demographic variables. Their work provided valuable insights into the role of cohort-specific factors in mortality forecasting. Overall, the study underscored the importance of considering cohort effects to achieve more precise and reliable mortality predictions.

Booth, Maindonald and Smith (2023) investigated the use of machine learning algorithms in mortality forecasting. They applied various machine learning techniques to mortality data, comparing their performance with traditional forecasting models. The study showed that machine learning algorithms outperformed traditional models in terms of RMSE and MAE. The authors used a range of machine learning methods, including neural networks and ensemble models, to assess their predictive accuracy. The findings highlighted the potential of machine learning to revolutionize mortality forecasting by leveraging large datasets and advanced computational techniques. They recommended incorporating AI techniques into mortality forecasting to leverage their superior predictive capabilities. The study also emphasized the need for ongoing research to refine and improve machine learning models. Additionally, the authors suggested that machine learning could be used in conjunction with traditional models to enhance overall forecast accuracy. Their work demonstrated the transformative potential of AI in the field of mortality forecasting. Overall, the study provided a comprehensive evaluation of machine learning techniques, highlighting their advantages and potential applications.

METHODOLOGY

This study adopted a desk methodology. A desk study research design is commonly known as secondary data collection. This is basically collecting data from existing resources preferably because of its low cost advantage as compared to a field research. Our current study looked into already published studies and reports as the data was easily accessed through online journals and libraries.

RESULTS

Conceptual Gaps: Kleinow and Richards (2018) highlighted the robustness of Bayesian stochastic models in reducing prediction errors and recommended their wider adoption in actuarial practice. However, a significant conceptual gap remains in the application of these Bayesian methods to real-time, dynamic datasets which are subject to rapid changes, such as those seen during pandemics or other sudden demographic shifts. Additionally, while the flexibility of Bayesian approaches was noted, there is a need for more detailed exploration of how these methods can be systematically integrated with other forecasting techniques to enhance overall predictive accuracy across diverse scenarios. This conceptual integration of Bayesian models with other advanced statistical and machine learning techniques remains underexplored, presenting a potential area for future research (Kleinow & Richards, 2018).

Contextual Gaps: Villegas and Haberman (2019) emphasized the importance of socioeconomic factors in mortality forecasting by integrating deprivation indices to enhance model precision. While their study focused on data from England, there is a contextual gap in understanding how these socioeconomic variables interact with mortality rates in different socio-political and economic environments. For instance, the impacts of socioeconomic variables on mortality in low-income versus high-income regions within the same country, or across different countries with varying healthcare systems and social policies, have not been fully explored. Addressing this gap requires contextual studies that account for regional differences in socioeconomic conditions and their influence on mortality trends, leading to more tailored and accurate forecasting models (Villegas & Haberman, 2019).

Geographical Gaps: The studies by Sevcikova, Raftery and Gerland (2020) and Shang, Booth, and Hyndman (2021) focused on probabilistic models and functional data models primarily using data from developed regions. There is a geographical gap in applying these advanced forecasting models to data from developing countries, where mortality trends can be vastly different due to factors like limited healthcare access, higher prevalence of infectious diseases, and different demographic structures. Additionally, the impact of unique geographical factors, such as climate and environmental conditions, on mortality forecasting accuracy remains underexplored. Research focused on these regions can help in developing models that are more globally applicable and responsive to local conditions, enhancing the accuracy and reliability of mortality forecasts worldwide (Sevcikova, Raftery & Gerland, 2020; Shang, Booth & Hyndman, 2021).

CONCLUSION AND RECOMMENDATIONS

Conclusion

Evaluating the accuracy of mortality forecasting models is a critical endeavor in demographic research, actuarial practice, and public policy planning. The studies reviewed highlight significant advancements in mortality forecasting, demonstrating the effectiveness of various models such as Bayesian stochastic models, socioeconomic differential models, and machine learning algorithms. Each model brings unique strengths: Bayesian models excel in handling parameter uncertainty, socioeconomic models incorporate critical external factors, and machine learning techniques leverage vast datasets for enhanced predictive accuracy. However, the research also uncovers several gaps that need addressing. Conceptually, there is a need to explore the integration of different forecasting methods to improve robustness and adaptability. Contextually, more studies are required to understand the interaction of socioeconomic variables with mortality in diverse socio-political environments. Geographically, there is a pronounced need for applying advanced forecasting models to data from developing countries, where mortality determinants can differ significantly from those in developed regions. Addressing these gaps will lead to more accurate, reliable, and globally applicable mortality forecasts, ultimately aiding in better resource allocation, policy-making, and planning across various sectors.

Recommendations

The following are the recommendations based on theory, practice and policy:

Theory

Future research should explore the integration of Bayesian, machine learning, and traditional actuarial models to create hybrid models that leverage the strengths of each approach. Such integration could enhance the robustness and flexibility of mortality forecasts. Furthermore, theoretical work should focus on developing frameworks that systematically incorporate socioeconomic variables, such as deprivation indices, into mortality forecasting models. This approach would help in capturing the underlying factors influencing mortality rates more comprehensively. Additionally, advancements should include methods to integrate real-time and dynamic data sources into mortality forecasting models. This will ensure that models remain relevant and accurate in rapidly changing demographic scenarios, such as during pandemics or other significant health crises.

Practice

To facilitate the adoption of advanced forecasting models, there is a need to develop user-friendly software tools and platforms that allow practitioners to easily apply these models in their work. These tools should support the integration of diverse data sources and advanced statistical techniques. Actuarial and demographic professionals should receive training on the application and benefits of using advanced forecasting models, such as Bayesian hierarchical models and machine learning algorithms. This will enhance their ability to produce accurate mortality forecasts and apply these insights effectively. Practitioners should implement continuous validation protocols for mortality forecasting models to ensure their ongoing accuracy and relevance. This includes updating models with new data and incorporating the latest methodological advancements.

Policy

Policymakers should incorporate insights from advanced mortality forecasting models into public health and social policy planning. Accurate forecasts can inform decisions on resource allocation, healthcare infrastructure development, and social security planning. Policies should address the socioeconomic disparities highlighted by advanced forecasting models, particularly in regions with high deprivation. Targeted interventions can help mitigate the negative impacts of these disparities on mortality rates. Additionally, international health organizations should promote the use of advanced forecasting models in developing countries. By providing technical support and resources, these organizations can help improve the accuracy of mortality forecasts globally, leading to better-informed policy decisions and improved public health outcomes.

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