IOCR 2026 Conference

The 1st International Online Conference on Risks

6–7 July 2026 | Online

MDPI

A Hybrid Framework to Model Insurance Mortality Rates: Graduation and Ensemble Models

Lobna Sayed Ahmed[1, 2*], María Isabel Martínez Torre-Enciso[1], Oscar Valdemar De la Torre-Torres[3]

[1] Department of Finance and Commercial Research, UDI of Finance, Faculty of Economics and Business, Universidad Autónoma de Madrid (UAM), Madrid 28049, Spain.

[2] Department of Insurance and Actuarial Science, Faculty of Commerce, Cairo University, Giza 12613, Egypt.

[3] School of Accounting and Management Sciences, Universidad Michoacana de San Nicolás de Hidalgo (UMSNH), Morelia 58090, México.

* Corresponding author: lobna.sayed@estudiante.uam.es | lobna.sayed@foc.cu.edu.eg

INTRODUCTION & AIM

Accurate mortality modeling is fundamental to life insurance pricing, reserving, and capital estimation. However, insurance mortality data, particularly in emerging markets, are often limited, noisy, and highly variable, making reliable mortality estimation and forecasting challenging. Traditional actuarial graduation methods provide interpretable mortality patterns but have limited predictive capabilities, whereas machine learning models can capture complex nonlinear relationships. This study proposes a hybrid framework that integrates actuarial graduation techniques with ensemble machine learning to improve the estimation and forecasting of insurance mortality rates.

Research Question: Can integrating actuarial graduation techniques with ensemble machine learning provide a robust framework for modeling and forecasting insurance mortality rates?

METHOD

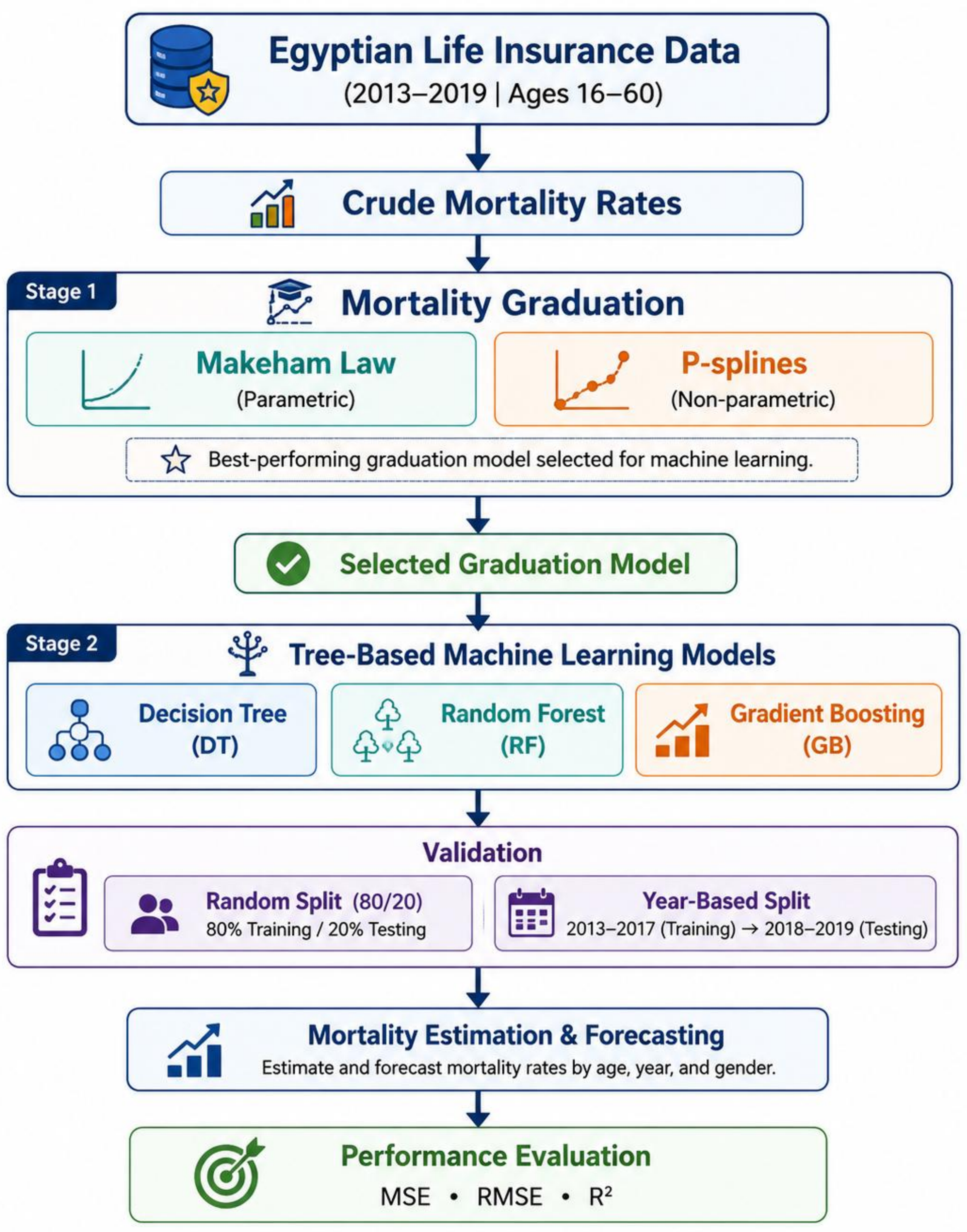
A two-stage hybrid framework was developed to estimate and forecast insurance mortality rates using Egyptian life insurance data (2013–2019).

Stage 1: Mortality Graduation
Crude mortality rates were smoothed using the Makeham Law and P-splines. The models were compared using MSE and BIC, and the best-performing model was selected.

Stage 2: Tree-Based Machine Learning
The graduated mortality rates were modeled using Decision Tree (DT), Random Forest (RF), and Gradient Boosting (GB).

Models were trained using age, year, and gender as predictors and evaluated under random (80/20) and year-based (2013–2017/2018–2019) validation strategies.

Predictive performance was assessed using MSE, RMSE, and R^2.



The proposed hybrid framework combines the interpretability of actuarial graduation with the predictive power of ensemble machine learning for insurance mortality modeling and forecasting.

CONCLUSIONS

- A hybrid actuarial-machine learning framework was proposed for insurance mortality modeling using Egyptian life insurance data.
- Among the graduation methods, **Makeham Law** provided the best fit and was selected as the input for machine learning.
- **Gradient Boosting (GB)** consistently achieved the highest predictive accuracy under both random and year-based validation, outperforming Decision Tree and Random Forest.
- The year-based validation provided a more realistic assessment of forecasting performance, highlighting the challenges of predicting future mortality trends.
- The proposed framework combines the interpretability of actuarial graduation with the predictive power of ensemble machine learning, providing an effective approach for mortality estimation and forecasting.

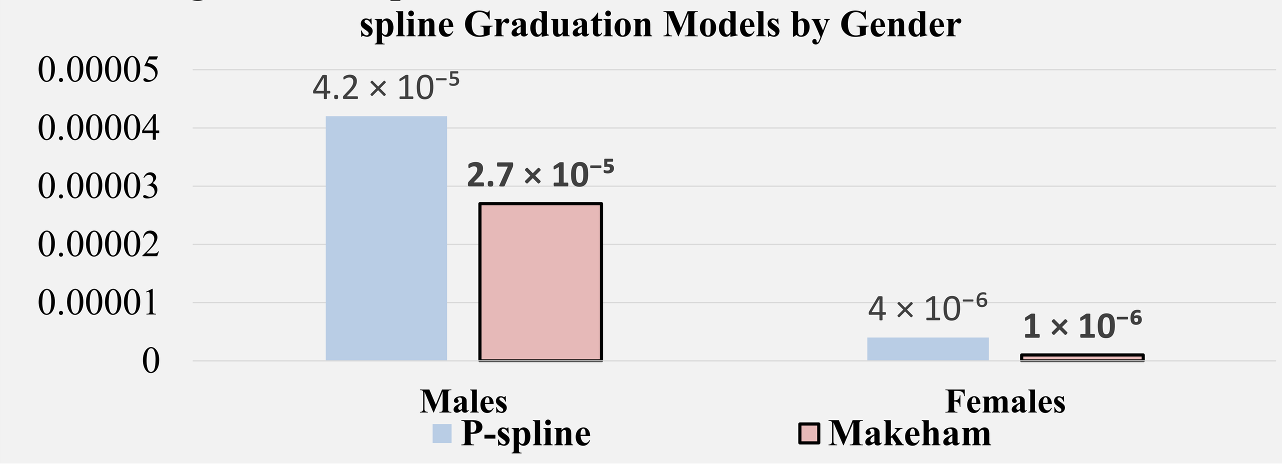
FUTURE WORK

- **Cross-regional validation:** Apply the proposed hybrid framework to insurance mortality data from other emerging markets to evaluate its robustness and generalizability.
- **Deep learning integration:** Extend the framework by investigating Bayesian neural networks for mortality forecasting and uncertainty quantification.
- **Probabilistic mortality forecasting:** Develop probabilistic forecasting models to better quantify uncertainty in future mortality projections

RESULTS & DISCUSSION

Mortality Graduation
The **Makeham Law** outperformed the **P-spline** model, achieving lower **MSE** and **BIC** values for both males and females. Beyond its superior statistical performance, the Makeham model more effectively captured the age-related increase in mortality while maintaining a simple and interpretable actuarial structure. Consequently, the Makeham-graduated mortality rates were selected for the machine learning stage.

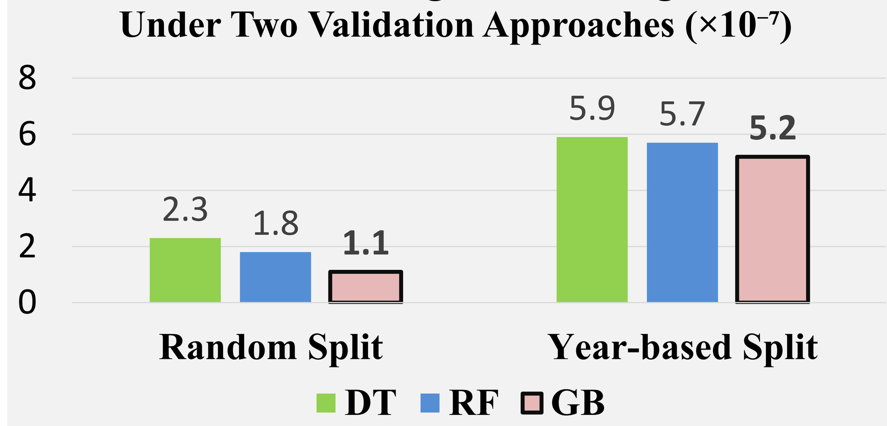
Figure 1: Comparison of MSE Values for the Makeham and P-spline Graduation Models by Gender



Machine Learning Performance
Among the three tree-based models, **Gradient Boosting (GB)** consistently achieved the highest predictive accuracy under both **random** and **year-based** validation strategies. It produced the lowest prediction errors (MSE and RMSE) and the highest R^2 score on the test data, outperforming both **Random Forest (RF)** and **Decision Tree (DT)**.

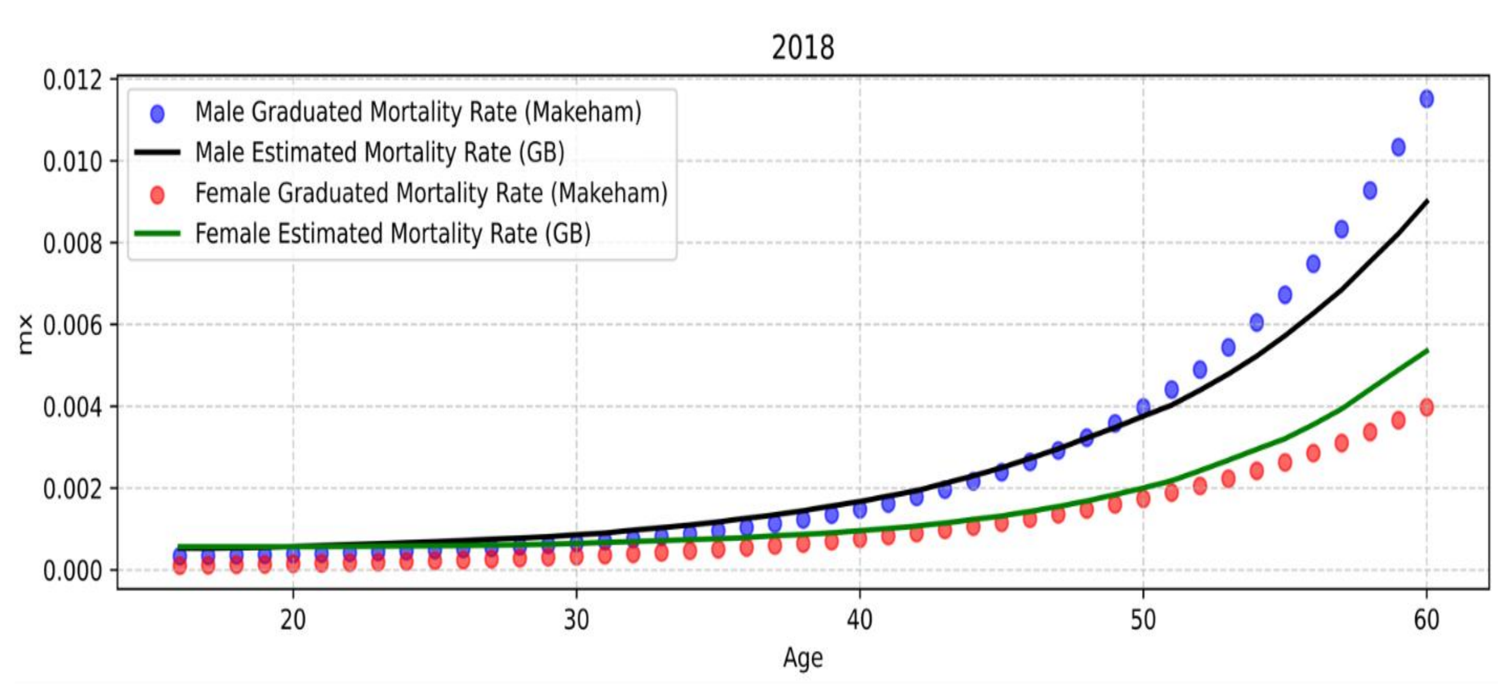
Gradient Boosting (GB) consistently achieved the lowest out-of-sample MSE across both validation strategies, confirming its superior predictive performance in modeling Makeham-graduated mortality rates.

Figure 2: Comparison of Tree-Based Machine Learning Models Using MSE Under Two Validation Approaches (×10⁻⁷)



Although prediction errors increased under the year-based split, reflecting the greater challenge of temporal forecasting, **Gradient Boosting** remained the best-performing model. These findings demonstrate that integrating actuarial graduation with ensemble learning provides a robust and reliable framework for estimating and forecasting insurance mortality.

Figure 3:Out-of-Sample Mortality Rate Predictions: Makeham-Graduated vs. Gradient Boosting for Both Genders (2018 Test Year)



REFERENCES/ACKNOWLEDGMENT

- Bjerre, D. S. (2022). *ASTIN Bulletin*, 52.
- Deprez, P., Shevchenko, P. V., & Wüthrich, M. V. (2017). European Actuarial Journal, 7(2), 337–352.
- Levantesi, S., & Pizzorusso, V. (2019). Risks, 7(1), 26.
- Su, D., Zheng, J., Shao, Y., Liu, J., Liu, X., Yu, K., Feng, B., Mei, H., & Qin, S. (2025). Digital Health, 11.
- Yue, J. C., Wang, H.-C., & Wang, T.-Y. (2019). North American Actuarial Journal, 25(Suppl. 1), S410–S420.

Acknowledgement: AI-assisted design tools were used to create the methodology infographic. The infographic was reviewed and refined by the authors. All scientific content, analyses, results, and conclusions presented in this poster are the original work of the authors.