



Transformation of Traditional Models to AI: SLR on the Application of Machine Learning in Mortality Prediction

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Abstract

The application of machine learning (ML) in actuarial science and life insurance has driven digital transformation in mortality risk prediction. This article conducts research using the Systematic Literature Review (SLR) methodology with the PRISMA approach to evaluate the performance comparison between ML methods and traditional actuarial models in predicting mortality risk. This study analyzed publication trends, geographic and institutional distribution, and methodologies used in the literature published between 2019 and 2025. The results from SLR show that ML methods, especially Random Forest and XGBoost, have superior predictive accuracy compared to traditional actuarial models such as Traditional Logistic Regression and Cox Proportional Hazards. However, despite the obvious accuracy advantage, issues of interpretability and long-term stability remain a major challenge in implementing ML in the actuarial industry. This study also identifies the need for a hybrid approach combining the strengths of both methodologies to improve prediction accuracy while maintaining high interpretability. This study suggests the need for further development in the application of ML by the regulation and compliance of the insurance industry. The findings provide insights for actuarial practitioners, regulators, and academics regarding the potential and challenges of using ML in mortality risk prediction.

Keywords: Machine learning, actuarial traditional model, hybrid model, mortality risk.

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1 Introduction

Machine learning (ML) in the current digital era encourages digital transformation in various spheres of life, including actuarial science and life insurance [1]. In life insurance, predicting the risk of death is the main thing in calculating premiums, which are traditionally modelled using mortality tables and the Lee-Carter model [2], which has shortcomings. So, to deal with these shortcomings, the machine learning (ML) method has the advantage of better prediction accuracy to deal with the complexity of modern mortality, which is influenced by several things, one of which is the risk of the COVID-19 pandemic [3]. In addition, machine learning (ML) methods, such as deep learning, random forest, and neural networks, can also overcome the challenges of capturing nonlinear relationships and complex interactions between risk variables in traditional models with a strong mathematical basis and good interpretability [4].

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Machine learning (ML) methods have some advantages in terms of predictions that are needed for the actuarial industry, but applying these methods still has major challenges. These challenges are interpretability in the context of actuarial and insurance, which is difficult to use because many algorithms in machine learning (ML) methods function as "*black boxes*" [5]. Not only that, limitations in long-term validation for insurance products, regulatory compliance with the government, and ethical considerations towards customers are also a challenge that needs to be resolved before machine learning (ML) methods are fully implemented [6]. Several studies have compared the performance of various machine learning (ML) methods with simple actuarial models in certain contexts in actuarial science. For example, the Lee-Carter model and recurrent neural networks (RNN) methods can be compared to predict mortality rates. However, few studies integrate the findings of various comparison studies related to the performance of machine learning (ML) methods with traditional techniques in predicting mortality risk.

This study was conducted to fill the gap with a systematic review (SLR) research method that uses the PRISMA methodology (Preferred Reporting Items for Systematic Review and Meta-Analysis) to conduct the review. The objectives of this SLR research are to analyze the performance trends of ML methods compared to the performance of traditional actuarial models in predicting mortality risk, identify patterns present in publications from year to year at specific publication year boundaries, analyze the geographic and institutional distribution of relevant publications, identify key journals that publish on this topic, explore the most frequently used methodologies for comparison, and identify any research gaps for future studies. Thus, through the results of this SLR, actuarial practitioners, regulators, and researchers or academics gain important insights into the development of the application of machine learning (ML) methods in the actuarial industry to reduce the gaps that traditional actuarial models have in mortality risk prediction—not forgetting while maintaining a strong mathematical basis and implementing good interpretability for mortality risk management in the current era.

2 Methods

2.1 Research Design

This research uses a Systematic Literature Review (SLR), which utilises the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) methodology [7] to conduct a comparative analysis of the performance of machine learning (ML) methods with traditional actuarial models in predicting mortality risk. The purpose of choosing this method is to obtain a comprehensive overview of the status of research on this topic at a specified time interval, because SLR can systematically organise and synthesise research evidence.

2.2 Search Strategy

Specifically, this study used the Scopus database as a platform in the literature search conducted in February 2025. The search string used was (("machine learning" OR "artificial intelligence" OR "deep learning" OR "predictive modelling") AND ("mortality prediction" OR "life insurance" OR "insurance risk" OR "actuarial science" OR "actuarial models" OR "mortality tables")). The search string was developed based on the PICOS (Population, Intervention, Comparison, Outcomes, and Study Design) framework to identify literature relevant to this study's research question.

2.3 Inclusion and Exclusion Criteria

Studies selected for further review in this study were based on inclusion and exclusion criteria. The inclusion criteria set were publications in the range of 2019 – 2025, journal articles that were in English and had open access, and studies that directly compared machine learning (ML) methods with traditional actuarial models and focused on mortality risk prediction. The

exclusion criteria were studies without direct comparison between ML methods and traditional actuarial models; study types other than English journal articles, and articles that did not focus on mortality risk prediction. Inclusion and exclusion criteria were chosen to serve as the boundaries of this study, although they may introduce bias in selecting articles to be studied. The specific range of years between 2019 and 2025 is a time of rapid development in ML, making it a suitable range to look at trends. Language restriction was also made, and English was chosen because it is an international language that can unify the interpretation of understanding and avoid terminology inequality. Other criteria were determined according to this research topic and to increase the homogeneity of the sample to be studied.

2.4 Study Selection Process

The study selection is carried out in three stages, according to the recommendations of the PRISMA methodology. The first stage is the selection, which is performed by applying several filters to the Scopus database using the predetermined search string. The filters set in this study selection are the year of publication (2019 – 2025), the type of document, which is an article, the stage of publication that has been finalised, the type of source in the form of journals, English-language studies, and open access. Based on the entire application of the filter, it resulted in 634 articles from 1,404 studies. From these 634 articles, the second stage of selection was carried out. Namely, the selection was carried out by the predetermined inclusion and exclusion criteria, resulting in 25 articles that directly discussed the comparison of the performance of the ML method with traditional actuarial models in predicting mortality risk.

2.5 Data Extraction

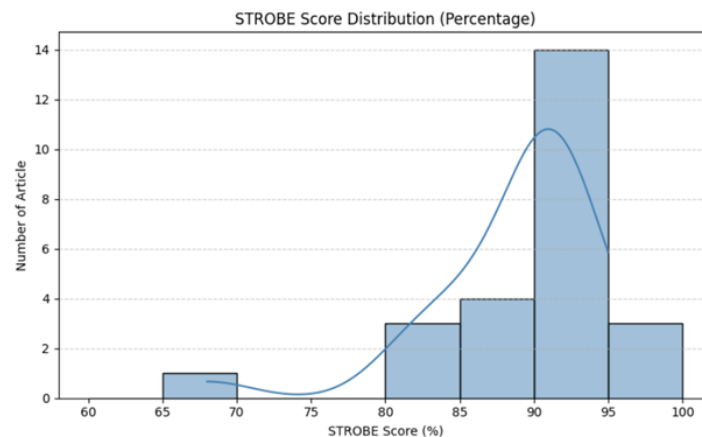
The 25 selected articles from the study selection exercise were extracted using a structured template that included publication information (author, year, title, journal, citations), methodology (dataset, sample size, observation period), methods compared (types of ML methods and traditional actuarial models), comparison results (performance metrics and values), application context (medical, insurance), interpretability and implementation aspects, and main conclusions. This structured template was implemented to make it easier to obtain a comprehensive overview of the research status of this topic.

2.6 Quality Assessment

This study used STROBE (Strengthening the Reporting of Observational Studies in Epidemiology) criteria [8] to assess the quality of 25 articles that had passed the study selection process. With a total of 22 STROBE criteria, namely title and abstract, introduction (background/rationale and objectives), methods (study design, setting, participants, variables, data sources/measurement, bias, study size, quantitative variables, and statistical methods), results (participants, descriptive data, outcome data, main results, and other analyses), discussion (key results, limitations, interpretation, generalisability), and other information (funding), the study results were divided into three categories. Categorisation is done with a certain value standard, namely high-quality category studies ($\geq 80\%$), medium (60%–79%), or low ($< 60\%$), based on 22 STROBE criteria relevant to research on this topic. Table 1 shows examples of 5 articles assessed based on the STROBE criteria, and Figure 1 shows the STROBE score distribution.

Table 1: Example of Article Assessment based on STROBE Criteria

No	STROBE Criteria	Article 1	Article 5	Article 15	Article 20	Article 25
Title and abstract						
1.	Title and abstract	✓	✓	✓	✓	✓
Introduction						
2.	Background/rationale	✓	✓	✓	✓	✓
3.	Objectives	✓	✓	✓	✓	✓
Methods						
4.	Study Design	✓	✓	✓	✓	✓
5.	Setting	✓	-	✓	✓	✓
6.	Participants	✓	-	✓	✓	✓
7.	Variables	✓	✓	✓	✓	✓
8.	Data sources/ measurement	✓	✓	✓	✓	✓
9.	Bias	-	-	-	-	-
10.	Study size	✓	-	✓	-	✓
11.	Quantitative variables	✓	✓	✓	✓	✓
12.	Statistical Methods	✓	✓	✓	✓	✓
Results						
13.	Participants	✓	-	✓	-	✓
14.	Descriptive Data	✓	-	✓	✓	✓
15.	Outcome data	✓	✓	✓	✓	✓
16.	Main results	✓	✓	✓	✓	✓
17.	Other analyses	-	-	✓	✓	✓
Discussion						
18.	Key results	✓	✓	✓	✓	✓
19.	Limitations	✓	✓	✓	✓	-
20.	Interpretation	✓	✓	✓	✓	✓
21.	Generalizability	✓	✓	✓	✓	-
Other Information						
22.	Funding	✓	✓	✓	✓	-
Total		91%	68%	95%	86%	82%

**Figure 1:** STROBE Score Distribution of 25 Selected Articles

2.7 Data Analysis and Synthesis

Data analysis was conducted with several approaches. The first approach was to analyze the performance comparison between ML methods and traditional actuarial models based on various metrics, including AUC, accuracy, and C-Index. The second approach is bibliometric analysis, which includes publication trends, geographical and institutional distribution of research, citation patterns and major journals based on the collected study data. The third analysis is a methodological analysis to determine the distribution of the number of ML methods and

traditional actuarial models often used in comparison and their application context. Based on these three analyses, research gaps will be identified, and the gaps in the literature on this topic will be analyzed to provide better direction for future research. All analysis results are visualised in graphs and diagrams to facilitate the interpretation and communication of the findings, ranging from PRISMA diagrams, publication trend charts, and other visual representations relevant to this research.

2.8 Data Visualization

Data visualization in this research is applied to facilitate more effective interpretation and communication of findings. The data visualization carried out in this study is a PRISMA diagram in the form of a flow chart describing the entire study selection process, a temporary trend graph related to the publication of the comparison of the ML method with the actuarial model in the form of a bar graph, heat maps that visualize the geographical distribution of the most productive countries contributing articles, data tables that present a comparison of the methods used for each article, bar graphs as visualizations comparing ML methods with traditional actuarial models, line graphs showing the results of methodological evolution analysis, performance metrics between methods in the form of dot plots, spider charts visualizing the strengths and weaknesses of ML methods and traditional actuarial models on various dimensions, and plots of identified research gaps in the form of bar graph visualizations.

2.9 Limitations of the Methodology

Applying the SLR research method with the PRISMA methodology to this study made an attempt to apply a comprehensive and systematic methodology. However, there are still some limitations that need to be recognized. These limitations are that the studies used for research only come from the Scopus database, examining English-language articles, methodological heterogeneity between studies that limit the ability to make direct comparisons, potential selection bias in the inclusion or exclusion criteria set, temporal limitations on publishing articles from 2019 – 2025, and the possibility of dominance of certain authors or institutions. To overcome all these limitations, the researchers ensured maximum transparency in the methodology documentation and ensured careful interpretation of the results.

3 Results and Discussion

3.1 Research Results

3.1.1 Selection Process and Study Characteristics

Based on the Scopus database with a search string determined based on the PICOS framework, there are 1,404 relevant studies. From the 1,404 studies, screening was then carried out by applying several filters, namely year of publication (2019 – 2025), the type of document, namely the article, the final publication stage, the type of source in the form of journals, English-language studies, and open access, which resulted in 634 articles. Next, a selection was made based on the inclusion and exclusion criteria established. This selection process resulted in 25 articles comparing the ML method with traditional actuarial models. A flowchart of the application of the PRISMA methodology that illustrates the study selection process is presented in [Figure 2](#).

The publication time trend shows a steady increase in research on this topic. From no explicit comparison of ML methods with traditional actuarial models in 2019, it increased to four articles in both medical and insurance contexts in 2020. And again experienced an up-and-down pattern in the interval 2021 – 2024 with a total of six articles in 2021, then decreased in 2022 to a total of five articles, and increased again in 2023 with six articles, followed by a decrease in the number to three articles in 2024 and no relevant research in 2025 when data collection was

carried out in this study for both medical and insurance contexts. This trend is visualized as a line chart according to context (medical or insurance) presented in Figure 3. It can be seen that the medical context excels with 19 articles compared to the insurance context, which only published six articles. Nonetheless, this trend still indicated an increasing interest in comparative analysis of this topic over the past five years.

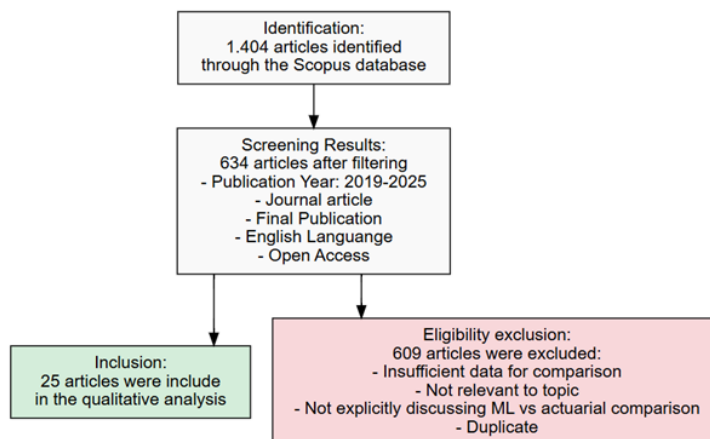


Figure 2: PRISMA Diagram of the Study Selection Process

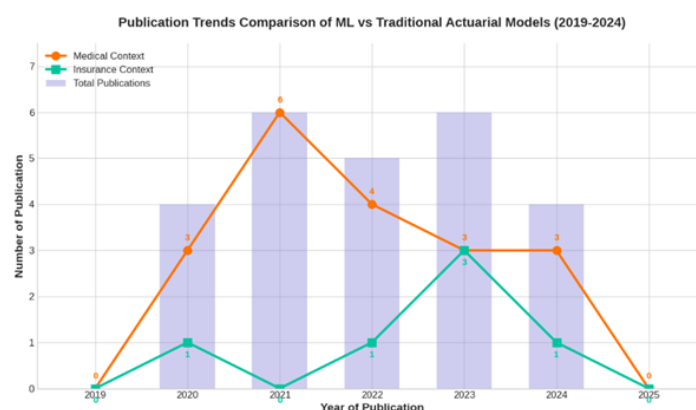


Figure 3: Publication Trend of ML Method Comparison with Actuarial Model

For the STROBE quality assessment, several important findings emerged. The first important finding was the variation in the studies' quality. There are 96% of articles used in this study that showed good quality based on the 22 STROBE criteria set. Based on this, the consistent strength of each article is that it describes the basic elements, such as the objectives and statistical methods used, well, and reports the main findings. Although all articles had good, consistent strengths, they did have systematic weaknesses, particularly in reporting potential biases in the research. A further finding was that several factors could affect the quality of the comparisons made in the articles, such as the large sample sizes and the contexts used. In addition, temporal trends were also a finding that influenced this STROBE assessment, as recent studies have shown a polarization in article strength that balances an increasing number of high-quality studies compared to low-quality studies. Finally, there are findings related to methodological limitations in addressing bias and generalizability that influence which models should be applied in practice. Based on the findings and assessment of these various aspects, three categories can be concluded, with each number of articles included, namely 24 high-quality articles, one medium-quality article, and no low-quality articles.

There is a dominance of Europe (44%) and international collaboration (36%), with a high percentage for geographical distribution. Followed by Asia, North America, and Africa with a

fairly low rate of 12%, 8%, and 4% respectively. The most productive institution contributing articles on this topic is Seoul National University, with two published articles. The other articles came from various leading universities, including the University of Oxford, the University of Cambridge, and the National University of Singapore, each contributing 1 article. This geographical distribution is presented in Figure 4. The journal that most frequently publishes on this topic is BioMed Central (BMC), with four articles published, although with different branches of health science. Based on the data, 68% of the journals that published this topic focused on healthcare, followed by 12% in insurance and 20% in other fields.



Figure 4: Geographic Distribution of the Most Productive Institutions Contributing Articles

3.1.2 Method Comparison

Table 2 presents the distribution of methods compared to the 25 articles that have passed the selection process. The most frequently used ML methods for comparison are Random Forest (20%) and Extreme Gradient Boosting (XGBoost) (13%). Other methods that can be considered to be used as a comparison are the Decision Tree method (7%), Recurrent Neural Networks (RNN) (7%), Gradient Boosting Model (GBM) (7%), Support Vector Machine (SVM) (6%), and developed methods such as Elastic Net, TabNet, GT-A Model, and AutoML (2%). As for traditional actuarial models, the most frequently used model is Traditional Logistic Regression (31%). Several other models can be considered for use in comparing with ML methods, namely the Cox Proportional Hazards (19%), Generalized Linear Model (GLM) (16%), Lee-Carter Model (6%), and other prediction models specifically used in the medical field, including Lung Allocation Score (LAS) and Clinical Risk Index for Babies II (CRIB-11) (3%). The most frequently used methods for comparisons, according to context, produce different results depending on the context. For the medical context, Random Forest (58%) and Traditional Logistic Regression (47%) dominated, while for the insurance context, Gradient Boosting Machine (GBM) (33%) and Generalized Linear Models (GLM) (50%) were the most used. The results of this context-based method comparison are presented in Figure 5.

Table 2: Distribution of Methods in the 25 Articles Examined

No	Author (Year)	Citation Number	Machine Learning Method	Traditional Actuarial Model
1	Boo, Y & Choi, Y (2020) [9]	17	Multilayer Perceptron (MLP), Decision Tree	Traditional Logistic Regression
2	Bithew et al. (2020) [10]	22	Random Forest, Logistic Regression, K-Nearest Neighbors (KNN)	Traditional Logistic Regression
3	Maier et al. (2020) [11]	15	Random Survival Forest (RSF)	Cox Proportional Hazards Model
4	Lee et al. (2021) [12]	30	LASSO, Ridge Regression, Elastic Net, Random Forest, SVM, XGBoost	TIMI, GRACE, ACTION
5	Li et al. (2021) [13]	18	Random Survival Forest (RSF)	Cox Proportional Hazards
6	Lee et al. (2021) [14]	16	Random Forest	CRIB-II, Traditional Logistic Regression
7	Brahmbhatt et al. (2022) [15]	15	LASSO, Random Forest	LAS Model (clinical model)
8	Garcia-Montemayor et al. (2020) [16]	12	Random Forest	Traditional Logistic Regression
9	Sinha et al. (2023) [17]	10	Random Forest, Neural Networks, XGBoost, Weighted SVM	EuroSCORE II, Traditional Logistic Regression
10	McDonnell et al. (2023) [18]	35	TabNet, XGBoost	Traditional Logistic Regression
11	Shen et al. (2024) [19]	3	GT-A (GNN + Transformer)	Lee-Carter Model
12	Chen & Khaliq (2022) [20]	7	RNN (LSTM, BiLSTM, GRU)	Lee-Carter Model
13	Clemente et al. (2023) [21]	6	Gradient Boosting Model (GBM)	Generalized Linear Model (GLM)
14	Vagliano et al. (2022) [22]	5	AutoML	Traditional Logistic Regression
15	Nakamura et al. (2022) [23]	4	RNNSurv, DeepSurv	Cox Proportional Hazard
16	Nistal-Nuño (2022) [24]	11	TE, Random Forest, XGBoost, Naïve Bayes, Bayesian Network	Traditional Logistic Regression
17	Chia et al. (2021) [25]	9	Decision Tree	Cox Proportional Hazards, Traditional Logistic Regression
18	Chou & Ghimire (2021) [26]	8	Random Forest	Linear Regression
19	Lopes et al. (2023) [27]	4	XGBoost	Traditional Logistic Regression
20	Andrade & Valencia (2023) [28]	4	Fuzzy Random Survival Forest (FRSF)	Cox Proportional Hazards
21	Kovacs et al. (2021) [29]	3	Decision Tree	Generalized Linear Model (GLM)
22	Penny-Dimri et al. (2023) [30]	3	Decision Tree, Random Forest, GBM	Cox Proportional Hazards
23	Huber et al. (2023) [31]	2	Random Forest, SVM, XGBoost	Traditional Logistic Regression
24	Wilson et al. (2024) [32]	1	GBM, Artificial Neural Networks (ANN)	Generalized Linear Model (GLM)
25	Kagerbauer et al. (2024) [33]	1	Random Forest, GBM, XGBoost, Deep Learning, Stacked Ensembles	Generalized Linear Model (GLM)

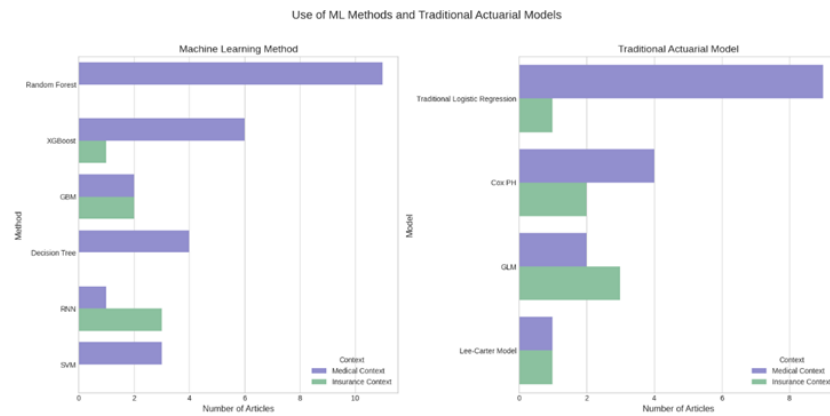


Figure 5: Comparison of Methods Based on Context

The methodological evolution analysis in this study identified three phases of development. The initial study in the interval 2019 – 2021 indicated more comparisons between the Random Forest and the Traditional Logistic Regression. Then, there was a change in the second phase in 2022 – 2023, which showed an increase in the Traditional Logistic Regression and the Cox Proportional Hazards used as a comparison. The last phase, the most recent period, 2024 – 2025, shows the emergence of the Generalized Linear Model (GLM), which is starting to be used and compared with the Gradient Boosting Machine (GBM), especially in the insurance context. In addition, a hybrid approach uses two methods at once by integrating the strengths of ML methods and traditional actuarial models starting in 2022. A visualization of the results of the methodological evolution analysis in this study is presented in Figure 6.

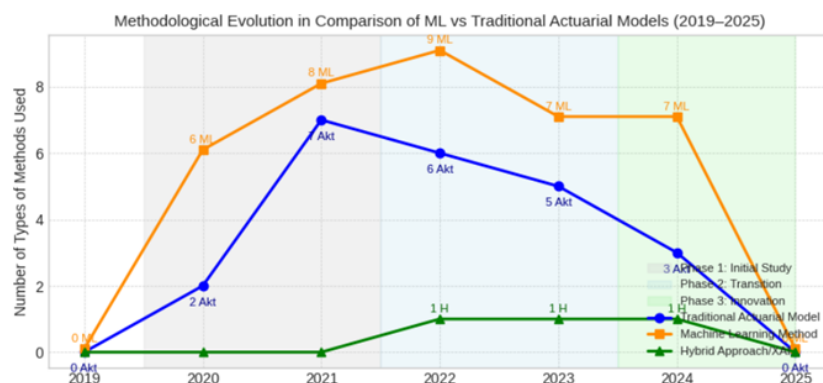


Figure 6: Methodological Evolution Analysis Results

3.1.3 Performance Comparison

Of the 25 articles that have gone through the selection process, 60% of the total articles state that the machine learning method is far superior. While 16% of the 25 articles show the opposite result, namely, the traditional actuarial model is far superior, and the remaining 4% show the result that there is no difference in mortality prediction results using ML methods and traditional actuarial models. Based on the visualization in Figure 7, it can be seen that, in general, the ML method is far superior based on the accuracy (59.2%), sensitivity (35.8%), mean absolute error (MAE) (22.2%), Area Under the Curve (AUC) (17%) values, which are more significant. However, if focused on the context, the results will vary. For the medical context, the ML method excels based on the increase in accuracy (59.2%) in the death rate scenario. Another thing with the insurance context that gives varied results is that the ML method is far superior for short-term mortality projections, which is inversely proportional to the traditional actuarial model, which is superior for

245 long-term mortality projections.

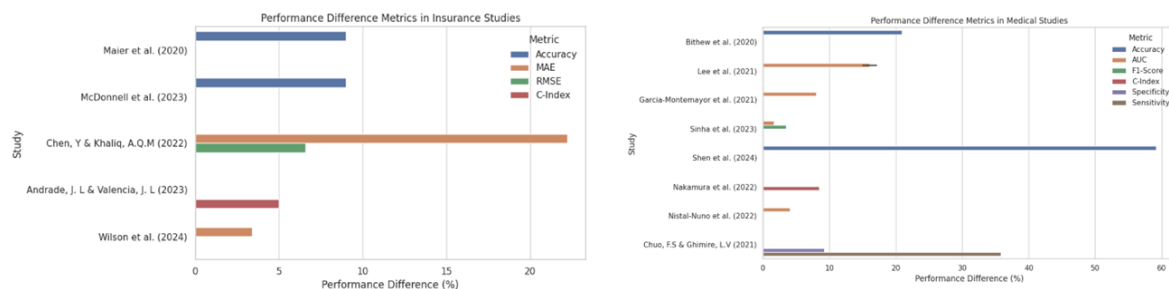


Figure 7: Performance Metrics Between ML Method and Traditional Actuarial Models

246 3.1.4 Relative Strengths and Limitations

247 To review this section, several aspects compare the ML method and traditional actuarial models:
 248 data requirements, interpretability, predictive accuracy, adaptability, regulatory compliance,
 249 long-term stability, capturing non-linearities, and computational complexity. ML methods and
 250 traditional actuarial models have different relative strengths and limitations. For the ML method,
 251 it has advantages in terms of predictive accuracy (85/100), computational complexity (60/100),
 252 capturing non-linearity (90/100), data requirements (70/100), and adaptability (80/100). These
 253 advantages go hand in hand with weaknesses in interpretability (35/100), regulatory compliance
 254 (45/100), and long-term stability (60/100)—the advantages and disadvantages of the traditional
 255 actuarial model. The strengths of the traditional actuarial model were long-term stability
 256 (85/100), regulatory compliance (85/100), and interpretability (90/100), while the weaknesses
 257 were computational complexity (15/100), data requirements (30/100), capturing non-linearity
 258 (20/100), adaptability (50/100), and precision accuracy (65/100). The relative strengths and
 259 limitations were visualized using spider charts presented in Figure 8.

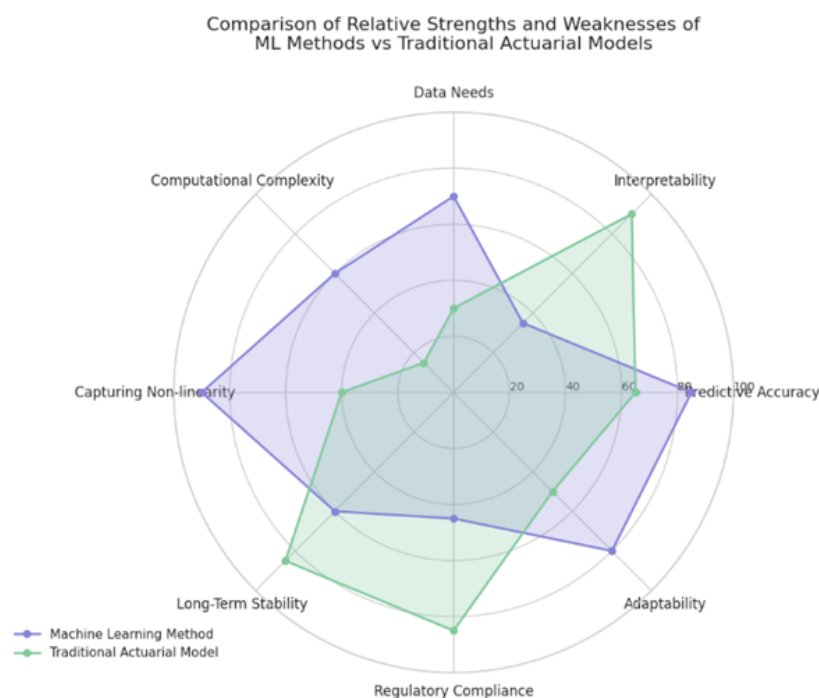


Figure 8: Comparison of Relative Strengths and Weaknesses

3.1.5 Research Gaps

Of the 25 articles examined, there are some underdeveloped research analyses in certain areas, which are commonly referred to as gaps. Methodological gaps refer to limited comprehensive external validation in 68% of the articles, limited predictive evaluation in homogeneous populations in 72% of the articles, and limited testing in homogeneous populations in 64% of the articles. The technical side of the gap refers to the need for a systematic hybrid approach (88%), better bias reduction methods (20%), and model calibration for the risk of tail events in a prediction (32%). The implementation gap refers to an insufficient regulatory framework for ML methods in actuarial science (32%) and limited cost-benefit analysis due to certain factors (40%). The interpretability gap refers only to the methods used to interpret complex ML models (60%). All of these gaps are presented in Figure 9, which concludes that there is a significant need for further research on this topic.

3.2 Discussion

3.2.1 Interpretation of Main Findings

Based on the identification using the SLR method, there are several consistent patterns in comparing the performance of the ML method with traditional actuarial models in predicting mortality risk. The most important finding in this study is that the ML method is far superior in 60% of the articles compared to the traditional actuarial model. This result suggests good potential for this methodology to improve the accuracy of predicting mortality risk. However, when narrowed down by context (medical or actuarial), the results suggest that the superiority of ML methods is uneven for each context. In particular, ML methods consistently excel in the medical context, especially for Random Forest and Extreme Gradient Boosting (XGBoost) methods that can capture the complexity and non-linearity of medical data well. In contrast, the more moderate and variable superiority in the insurance context, especially for long-term projections, makes the traditional actuarial model the winner, with the Cox Proportional Hazards model as the representative in predicting mortality risk.

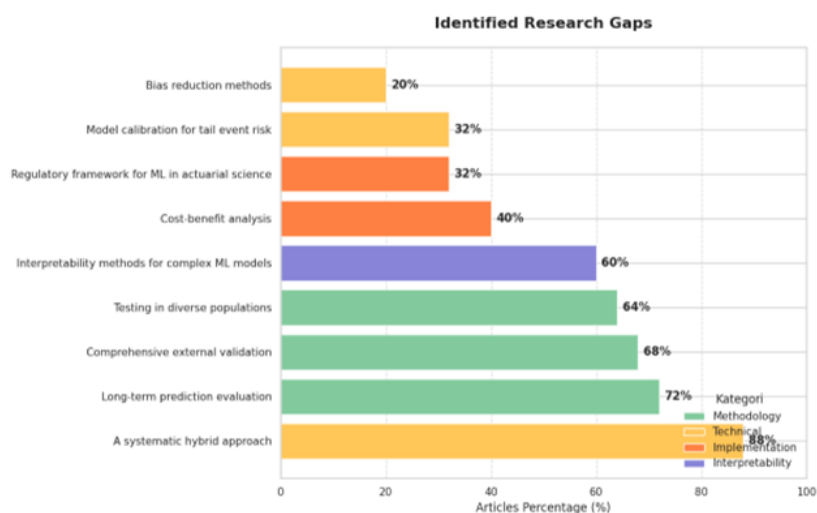


Figure 9: Plot of Identified Research Gaps

An interesting result of this comparative study is the dominance of Random Forest over Traditional Logistic Regression and Gradient Boosting Machine (GBM) over Generalized Linear Model (GLM), especially in 2024. The advantage of the Random Forest lies in its inherent balance between high prediction accuracy and reasonably good interpretability. These advantages are compared with the advantages of Traditional Logistic Regression, which remains the standard

in survival analysis because it has a fairly complex computation, which makes the comparison between the two interesting.

3.2.2 Accuracy and Interpretability Challenges

When choosing a methodological approach, an actuarial practitioner would consider predictive accuracy and interpretability. Based on this research, ML methods excel in accuracy but have poor interpretability scores, especially for Deep Learning methods, due to their "black box" nature. Interpretability is an important aspect of actuarial analysis. That is why only a few ML methods can be used in the actuarial industry. It cannot be denied that in the context of the insurance industry, transparent decisions that can be explained and defended objectively are needed. Thus, traditional actuarial models are still maintained today. This is due to the relatively higher level of interpretability in predicting mortality risk. In addition, traditional actuarial models still maintain regulatory compliance. However, based on the methodological evolution results identified, many researchers are trying to resolve this gap and realize that in the future, predictions can be made not only with one methodology but by combining the strengths of both.

3.2.3 Implications for Practice and Research

The results of this study have important implications for various stakeholders in the actuarial and insurance world in predicting mortality risk. For actuarial practitioners, the results state that ML methods significantly improve prediction accuracy, although they must still consider specific needs, such as short-term predictions or contexts with complex data. As for the needs in long-term applications that require high interpretability, traditional actuarial models are a better choice. However, it is interesting that 88% of the articles identified the need for a systematic hybrid approach to improve the quality of mortality risk prediction. Thus, actuarial practitioners must master programming and AI to use ML methods that align with the times.

For regulators, keep in mind that technological developments will continue to advance, so it is necessary to develop new standards for interpretability and stability policies of machine learning methods in the actuarial industry, given the strength of these methods, by not forgetting to first conduct a review of the method to be applied. For researchers or academics, quite large research gaps occur from the SLR. Starting from the need for more comprehensive external validation, to better long-term evaluation. In addition, there are limitations in the interpretation of ML methods in the insurance world, which is a major highlight in the development of significant innovations in the future.

3.2.4 Strengths and Limitations of the Review

The main strength of this SLR is that it is a comprehensive search strategy with an in-depth analysis of 25 articles specifically comparing ML methods with traditional actuarial models. Other strengths include quality assessment using the STROBE instrument and systematic identification of research gaps. Behind these advantages, some limitations need to be recognized, namely the use of databases only from Scopus, the focus on English-language articles, the potential bias of publications that support the results of ML methods positively, and the relatively recent emergence of this research domain, which limits the long-term perspective.

3.2.5 Future Research Directions

Based on the research conducted using the SLR method, with several gaps identified, several promising research directions will be explored in the future. These research directions are the development of a hybrid approach that integrates the theoretical basis of traditional actuarial models with the predictive accuracy capabilities of the ML method in predicting mortality

risk. In addition, a multi-institutional external validation study assesses the generalizability of performance comparisons for each article published on this topic, so they have the same standards. Another research direction is the development of XAI (Explainable Artificial Intelligence) techniques in actuarial to overcome the gap between the advantages of ML methods and traditional actuarial models, so that ML methods can be used in the actuarial industry. Finally, an important research direction is to comprehensively analyze the adoption of ML methods in actuarial practice to take advantage of technological developments and improve accuracy in mortality risk prediction.

4 Conclusion

This study compares machine learning (ML) methods and traditional actuarial models in predicting mortality risk through a Systematic Literature Review (SLR) approach with the PRISMA methodology. Based on the analysis of 25 selected articles, it was found that ML methods, especially Random Forest and XGBoost, have superior prediction accuracy compared to traditional actuarial models such as Traditional Logistic Regression and Cox Proportional Hazards. However, the main challenges in applying machine learning (ML) methods are the low level of interpretability, difficulty in long-term validation, and compliance with insurance regulations, which are still obstacles to fully adopting this technology in the actuarial industry.

This study also found that while machine learning (ML) methods have shown advantages in the medical context, their application in the insurance industry still has limitations, especially in more accurate long-term mortality projections using traditional actuarial models. Therefore, a hybrid approach is needed that combines the strengths of machine learning (ML) methods in improving prediction accuracy with the advantages of traditional actuarial models in interpretability and regulatory compliance.

In addition, this study identified various research gaps that need to be further explored, such as the need for more comprehensive external validation, the development of bias reduction methods in prediction, and the use of Explainable Artificial Intelligence (XAI) techniques to improve the transparency of machine learning (ML) methods in life insurance. The implications of these findings highlight the need for clearer regulatory standards and the development of more adaptive prediction models to meet the needs of the actuarial industry in the digital era.

As a recommendation, future research could explore hybrid approaches that combine the interpretability of traditional actuarial models and regulatory elements with the higher predictive accuracy of machine learning (ML) methods. In addition, more studies are needed to assess the effectiveness of the XAI approach in increasing transparency and trust in ML models in the environment of the actuarial industry.

CRedit Authorship Contribution Statement

Vita Nuraini contributed to the methodology, formal analysis, writing - original draft, and visualization. Nina Fitriyati contributed to conceptualization, data curation, validation, writing – review & editing, supervision, and project administration.

Declaration of Generative AI and AI-assisted technologies

The author utilized the generative AI tool ChatGPT (version 4, OpenAI) to assist in the development of ideas, code generation, and LaTeX formatting. Additionally, Grammarly was employed to support grammar correction and the refinement of English language usage. All outputs produced by these tools were carefully reviewed and manually revised to ensure precision, originality, and adherence to academic standards.

Declaration of Competing Interest

The authors declare no competing interests.

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Data and Code Availability

The dataset was retrieved from Scopus.com and is publicly accessible. The visualizations were generated and executed using Google Colab.

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