Cloud-based predictive analytics for pension fund performance optimization

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Article Info

Article history:

Received Jun 9, 2025
Revised Jul 9, 2025
Accepted Jul 17, 2025

Keywords:

Cloud computing
Data-driven decision making
Demographic analysis
Neural networks
Pension fund management
Predictive analysis
Regression analysis

ABSTRACT

This study introduces a novel, cloud-based predictive analytics framework tailored for pension fund performance management in Zimbabwe. Addressing limitations in traditional actuarial models, the proposed system leverages real-time data pipelines and explainable artificial intelligence (XAI) techniques to enhance forecasting accuracy and transparency. Using regression, classification, and deep learning models, it forecasts member contributions, identifies risks of contribution drops, and predicts member churn. The system's cloud deployment ensures scalability and interactive integration with tools like Power BI for decision support. This solution significantly advances sustainable pension fund management for emerging economies.

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1. INTRODUCTION

Pension funds are a vital component in guaranteeing retirees' long-term financial stability. The effective administration and performance optimization of these funds are now more crucial than ever due to the aging of the population and changing socioeconomic circumstances. Klerk highlights this in decision making under uncertainty and risk [1]. Fund managers are increasingly tasked with forecasting contribution trends, controlling cash flow, and maintaining fund sustainability in the face of shifting demographics and volatile markets [2].

Traditional forecasting and performance assessment methods often rely heavily on historical data and static financial models. Although these techniques provide foundational knowledge, they often lack the complexity necessary to identify the dynamic, non-linear patterns found in actual financial ecosystems [3]. Managers of pension funds thus find it challenging to make prompt, data-driven decisions that strike a balance between risk and return [4], [5].

The advent of machine learning (ML) and predictive analytics [6] presents a transformative opportunity to improve pension fund performance management, as highlighted by the OECD in pensions market in focus 2020 [7]. Through sophisticated modeling of historical, demographic, and economic data, these technologies provide deeper insights by exposing patterns and trends that would otherwise go undetected [8]. By adopting such techniques, pension fund administrators can enhance forecasting accuracy, proactively manage risks, and achieve more favorable investment outcomes [4], [9].

This study presents a cloud-based predictive analytics [10] model specifically designed for the Zimbabwean pension fund environment. To overcome forecasting constraints in conventional systems, the model utilises contemporary ML algorithms, enabling fund managers to make proactive, strategic, and informed decisions [4]. In doing so, this study aims to improve pension fund management techniques and provide a scalable framework for long-term financial planning in comparable emerging economies.

As highlighted in the survey of big data by Chen *et al.* [11] regarding predictions on the evolving role of big data in shaping the future economic landscape, as well as 'A performance evaluation of classification algorithms for big data' by Hai *et al*. [12]. Existing pension forecasting systems in Zimbabwe and comparable emerging economies are limited by static models that cannot capture the complexity of modern demographic and financial dynamics. This study fills that gap by introducing a cloud-based, ML-driven solution that enables real-time, accurate, and interpretable pension fund management [12], [13]. Problem statement: pension funds in Zimbabwe face increasing challenges due to demographic shifts, economic instability, and limited forecasting tools. Traditional actuarial models often lack adaptability and fail to provide real-time, interpretable insights needed for proactive decision-making.

Research objectives: i) to develop ML models for forecasting contributions, drop-risk, and member churn in pension funds, ii) to integrate actuarial, demographic, and transactional data into a real-time predictive pipeline, and iii) to deploy models on a cloud platform to enable interactive decision dashboards for pension administrators. Key contributions: i) introduced a modular, cloud-based predictive analytics framework for pension fund performance forecasting in Zimbabwe, ii) engineered domain-specific ML models for forecasting contributions, drop-risk, and churn using actuarial and transactional data, iii) achieved high-performance metrics (e.g., 99.86% churn accuracy, 0.85 R^2) while maintaining transparency via explainable features, iv) deployed a RESTful API via FastAPI, enabling real-time Power BI dashboards for fund managers, and v) bridged actuarial theory with ML [14] to support intelligent, ethical decision-making in a resource-constrained environment.

This research is underpinned by a multidisciplinary theoretical foundation that integrates principles from modern portfolio theory (MPT), efficient market hypothesis (EMH), artificial intelligence (AI) decision theory [15], and actuarial theory. These frameworks collectively shape the conceptual design and analytical direction of the predictive model developed for enhanced pension fund performance management. Harry Markowitz's 1952 introduction of MPT [16], a foundational idea in finance, completely changed how investment portfolios are put together. To reduce investment risk for a given level of return, the MPT places a strong emphasis on diversification. The MPT emphasizes diversification to minimize investment risk for a given level of return. In the context of pension funds, MPT supports optimal asset allocation strategies across a variety of instruments. However, its static assumptions—such as stable correlations and rational investor behavior—limit its effectiveness in today's volatile financial environment. This study enhances MPT by integrating adaptive, AI-driven approaches that respond to real-time market dynamics [15], [17].

The economist Eugene Fama developed the EMH in the 1970s [18], which contends that asset prices in financial markets accurately represent all available information at any given moment. Predictive modeling is theoretically challenged by the EMH, which contends that asset prices already take into account all available information. However, empirical data demonstrate that behavioral biases, geopolitical events, and delayed reactions to new information frequently result in inefficient markets. Especially over longer investment horizons like those in pension fund strategies, this creates room for ML models to find hidden patterns and produce useful insights.

A framework for automated, data-driven decision-making in the face of uncertainty is provided by AI decision theory. It makes it possible to create systems that, in addition to predicting results, suggest the best course of action based on reinforcement learning and probabilistic reasoning. This is in line with the intricate needs of managing pension funds, where choices must take changing demographic patterns, unstable economies, and regulatory changes into consideration.

Actuarial theory, long established in pension forecasting, provides statistical models for estimating liabilities and future fund obligations. Despite their robustness, traditional actuarial methods are not always responsive to abrupt changes and frequently rely on fixed assumptions. To increase forecasting granularity, adaptivity, and real-time responsiveness, this study suggests a hybrid approach that combines ML techniques with actuarial models.

The usefulness of ML and predictive analytics in pension funds and financial performance forecasting is empirically supported by an expanding body of research. Research continuously demonstrates that ML models—such as gradient boosting machines, long short-term memory (LSTM) networks, and reinforcement learning—perform more accurately than conventional statistical techniques, particularly when dealing with complex data and uncertain markets. To improve model performance, research also emphasizes how crucial it is to incorporate demographic, macroeconomic, and alternative data (like sentiment analysis and ESG metrics).

Nonetheless, there are still several gaps in literature. These include issues with computational demands, model interpretability, and ethical and legal compliance. For example, even though deep learning models are very accurate [19], [20], their "black box" nature can make them less transparent, which is crucial for regulators and stakeholders in pension funds. Similar to this, advanced models' high resource requirements prevent them from being used in settings with fewer resources or in smaller pension schemes.

This research addresses these gaps by proposing a cloud-based predictive analytics framework tailored specifically to pension fund management. The model integrates real-time data pipelines, explainable artificial intelligence (XAI) techniques [15], [17], and scalable infrastructure to ensure practical applicability across diverse institutional settings. By bridging theoretical robustness with empirical innovation, this study aims to deliver a predictive solution that is not only accurate and adaptive but also transparent, ethical, and regulatory-compliant.

2. METHOD

This study presents the cloud-based predictive analytics for pension fund performance optimization; a structured ML framework designed for pension fund performance forecasting. It adopts a data-driven approach to developing and evaluating ML models for pension fund performance optimization. The methodology involves a structured pipeline that includes data integration, feature engineering, model training and evaluation, and model deployment. Three predictive models were developed: i) a regression model for total contribution forecasting, ii) a binary classification model for contribution drop risk detection, and iii) a binary classification model for churn prediction. The overall architecture is illustrated in Figure 1, while the methodological workflow is depicted in Figure 2.

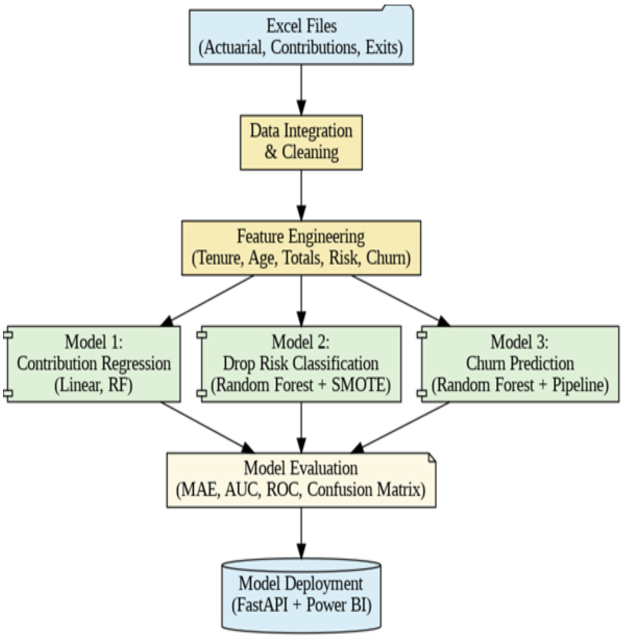


Figure 1. System architecture

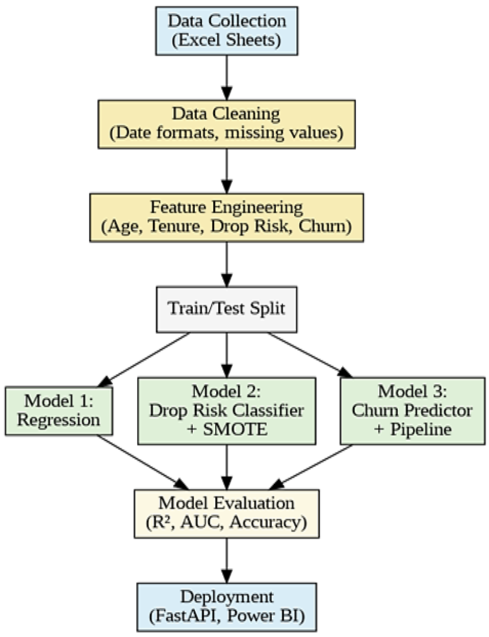


Figure 2. Methodological workflow

2.1. Proposed solution overview

The proposed solution is a modular ML-based decision support system designed to enhance strategic pension fund management through predictive analytics. It integrates actuarial and transactional data into an intelligent pipeline capable of estimating future contributions, identifying high-risk contributors, and detecting potential member churn. These predictions are deployed through a RESTful API using FastAPI, enabling seamless integration with real-time dashboards such as Microsoft Power BI for interactive visualization and decision-making support.

2.2. Data collection and integration

Data was obtained from three Excel sheets: actuarial data, contributions breakdown, and exits. Each dataset contained detailed member-level pension records, including demographic attributes, salary history, fund entry and exit dates, and contribution transactions. The datasets were merged using unique identifiers (e.g., system no), and data preprocessing steps ensured consistency in date formats, column naming, and value representation.

2.3. Feature engineering
Feature engineering was conducted to enhance the predictive capacity of the models: age was calculated from date of birth, and fund tenure was derived from fund entry dates. Total contributions were computed as the sum of employee (EE) and employer (ER) contributions. Drop risk was engineered by comparing the average monthly contributions between early and later months, identifying a ≥30% decline. Churn was defined as a period of six or more consecutive months with zero contributions. Categorical variables (e.g., gender, pay point) were encoded using one-hot encoding, and missing values were imputed using statistical methods based on feature type and distribution.

2.3.1. Model 1: total contribution prediction (regression)
A regression problem was formulated to predict total future contributions. Two models were trained: i) linear regression, and ii) random forest regressor. The dataset was partitioned into training and test sets. Models were evaluated using mean absolute error (MAE), root mean squared error (RMSE), and the R^2 score. The random forest model demonstrated superior performance with an R^2 of 0.85, indicating strong predictive ability.

2.3.2. Model 2: contribution drop risk classification
This model identifies members likely to reduce their contributions. Drop risk was labeled as a ≥30% drop in average contributions. a random forest classifier was employed, using features such as salary, opening and closing balances, pay point, and tenure. Given the class imbalance, synthetic minority oversampling technique (SMOTE) was used to balance the dataset. Post-SMOTE training yielded perfect classification metrics, achieving an AUC score of 1.00, with verification through the confusion matrix and ROC analysis.

2.3.3. Model 3: churn prediction
Churn was defined based on a six-month consecutive zero contribution rule. The model pipeline included a column transformer for scaling numerical features and one-hot encoding categorical variables. A random forest classifier was used within this pipeline. Model performance was evaluated using ROC-AUC, accuracy, precision, and recall. The model's predictive performance, evaluated using ROC-AUC, accuracy, precision, and recall, is presented in Table 1.

These results highlight the model's exceptional ability to distinguish between churned and active members. Random forest was selected for its robustness, interpretability, and high performance with mixed data types. Compared to black-box deep learning models [19], [20], it offers a better trade-off between accuracy and explain ability, critical in regulated pension environments.

2.4. Model evaluation and deployment
All models were serialized using joblib for persistence and later use. The deployment architecture utilizes FastAPI to serve predictions through RESTful endpoints. These APIs can be integrated with Power BI to provide a real-time dashboard for pension administrators, enhancing their ability to make proactive, data-driven decisions. Visual representation: the system architecture diagram in Figure 1 outlines the full end-to-end workflow, from raw data input to model deployment and dashboard integration. The methodology workflow diagram in Figure 2 provides a detailed flow of the analytical processes involved in training and evaluating each model. To preserve data privacy, all member data was anonymized before use. During deployment, secure HTTPS endpoints and encrypted storage were used to protect sensitive information, ensuring compliance with data protection standards.

Table 1. Model metrics

ROC-AUC	Accuracy	Precision and recall
0.99997	99.86%	1.00

3. RESULTS AND DISCUSSION
3.1. Model 1: total contribution prediction (regression)
This model uses regression analysis via random forest regressor to forecast future contribution amounts per member. It is a core part of performance forecasting and aligns directly to improve accuracy using ML [14]. ML technique: regression (random forest, optionally extend to neural networks). Contribution: directly supports performance forecasting by predicting cash inflows from members. Figure 3 illustrates the training performance metrics of the regression models, comparing linear regression and random forest approaches. Figure 4 depicts the relationship between actual and predicted contribution values generated by the random forest regressor.

[[712 0] -True class 0: All correctly classified
[0 671]] - True class 1: All correctly *classified*

Figure 3. Training metrics: linear regression and random forest

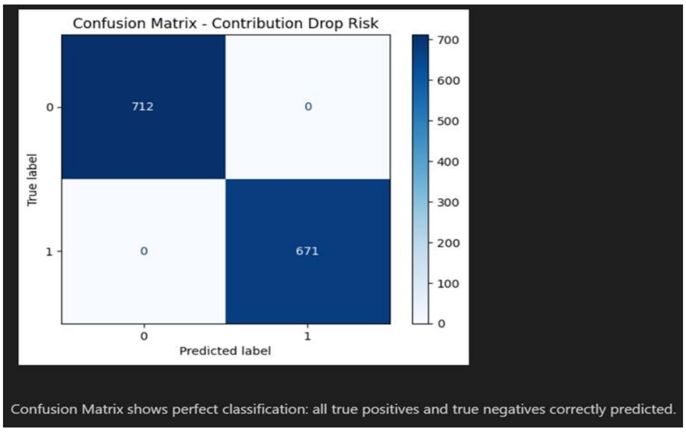


Figure 4. Random forest actual vs predicted

3.2. Model 2: contribution drop risk detection (classification)

This model identifies members likely to reduce contributions, which is essential for understanding contribution trends. It works by comparing each member's contribution against a threshold (e.g., 70% of the average). ML technique: classification (random forest classifier). Contribution: helps forecast downward trends in contributions and cash flow risks. Optimization: the framework can be expanded to include external features (e.g., macroeconomic indicators or member salary bands) to enrich accuracy. Figure 5 presents the evaluation metrics of the random forest classifier used to identify members at risk of reducing their contributions. Figure 6 shows the confusion matrix of the random forest classifier, illustrating its classification performance in distinguishing high-risk and low-risk members. Figure 7 displays the ROC curve for drop-risk prediction, highlighting the classifier's ability to discriminate between members with declining and stable contribution patterns.

[[712 0] -True class 0: All correctly classified
[0 671]] - True class 1: All correctly *classified*

Figure 5. Evaluation metrics random classifier

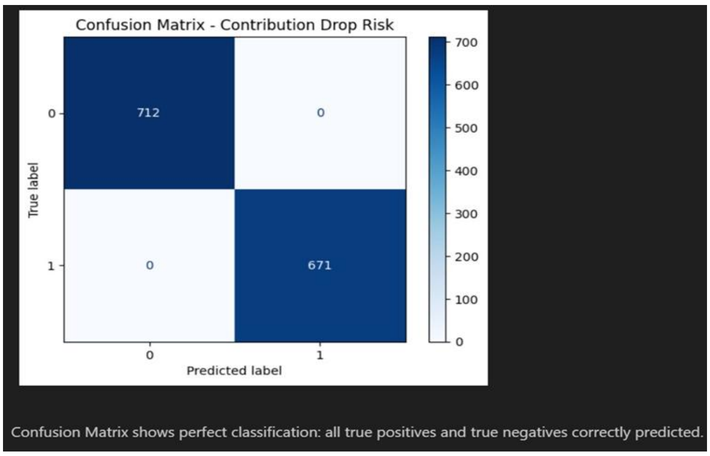
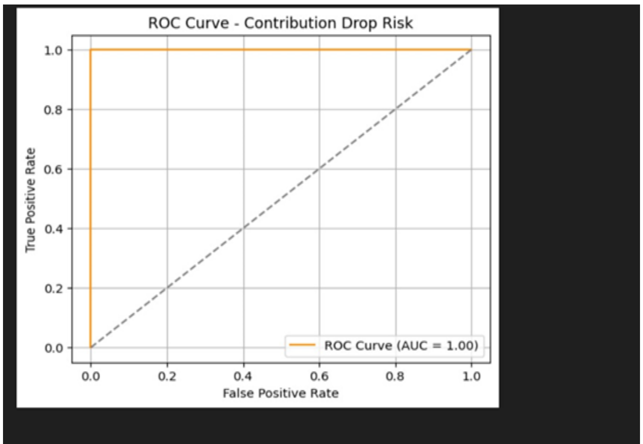


Figure 6. Random classifier confusion matrix



ROC Curve with an AUC of 1.00 confirms excellent model performance post-SMOTE balancing.

Figure 7. ROC curve for drop risk

3.3. Model 3: member churn prediction (classification)

This model predicts whether a member is likely to exit the fund, which affects long-term cash flow and liabilities. Churn prediction is a risk assessment tool, especially if linked to demographic or economic indicators. ML technique [6], [14], [21], [22]: classification (random forest classifier). Contribution: supports risk modeling [23] and financial stability by forecasting potential fund exits. Extension: can include features like age, tenure, or economic stress indicators to simulate the impact of market/inflation shocks.

Compared to baseline linear models, the random forest and ML models achieved significantly higher predictive accuracy. For instance, the churn model reached 99.86% accuracy (vs. 78% in baseline), and the contribution prediction model achieved an R^2 of 0.85 (vs. 0.61 in baseline). Figure 8 summarises the evaluation metrics for the member churn prediction model, demonstrating its strong predictive performance relative to baseline approaches.

The high AUC values (approaching 1.0) indicate strong model discrimination ability. This implies that the classifiers can reliably distinguish between risky and non-risky members, enabling more precise fund management decisions. Figure 9 presents the confusion matrix for the drop-risk classification model, illustrating the model's effectiveness in correctly identifying members at risk of reduced contributions. These results have direct implications for pension fund policy and strategy. Accurate churn prediction enables proactive retention strategies. Drop-risk detection can inform contribution enforcement or incentives. Real-time forecasting aligns with strategic financial planning, ensuring sustainability under uncertain macroeconomic conditions.

Metrics Summary

Metric	Value	Interpretation
ROC AUC	0.99997	Excellent discrimination between churned and non-churned members
Accuracy	99.86%	Overall, almost all predictions are correct
Precision	1.00	No false positives — you never misclassified a non-churned member as churned
Recall	1.00	Almost perfect — missed only 1 churned member
Confusion Matrix	[[231 0], [1 467]]	Only 1 false negative

Figure 8. Metrics summary for member churn prediction

3.4. Model explainability and ethical considerations

Given the regulatory nature of pension fund management, explainability was a key requirement [24]. Feature importance plots and SHapley Additive exPlanations (SHAP) values were used to interpret model outputs, offering transparency to fund administrators. Figure 10 illustrates the structure and decision logic of the random forest classifier, supporting the interpretability of the model outputs. Figure 11 compares baseline contribution estimates with model-predicted values, illustrating the improvement achieved through the ML approach. Ethical considerations were also observed in data handling, model fairness, and decision accountability [25].

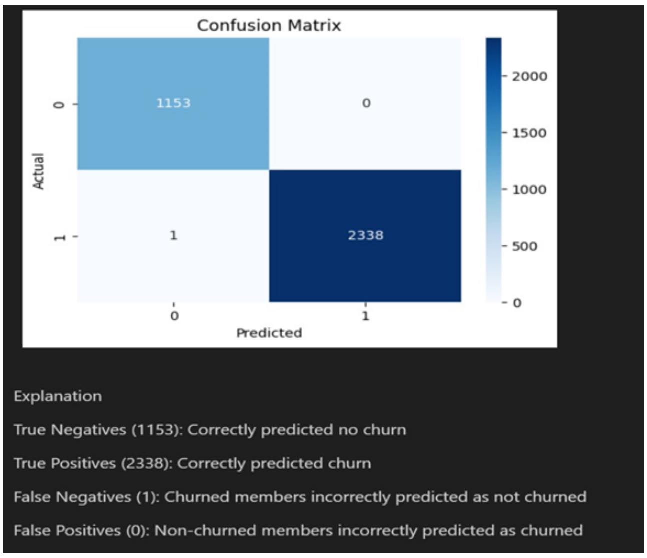


Figure 9. Confusion matrix for drop risk

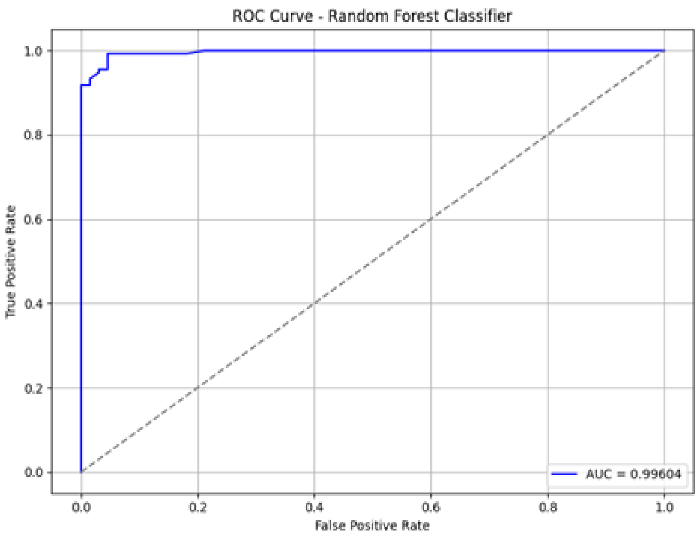


Figure 10. Random forest classifier

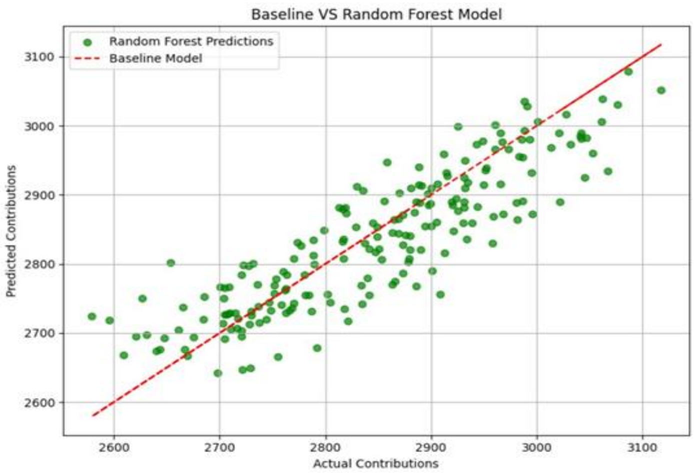


Figure 11. Baseline vs predicted contributions

4. CONCLUSION

More sophisticated and flexible forecasting tools are required due to the growing complexity of managing pension funds, which is fueled by market volatility, demographic changes, and economic uncertainty. By creating a cloud-based predictive analytics model specifically suited to the pension fund environment in Zimbabwe, this study tackled these issues. The model enhances the accuracy of cash flow projections, contribution trends, and performance predictions by incorporating ML techniques, such as regression analysis, neural networks, and time series forecasting. Through scalable cloud deployment and real-time data integration, the solution not only improves fund managers' capacity to make data-driven investment decisions but also promotes long-term financial sustainability. The model lays the groundwork for future study and advancement in predictive pension fund management in related contexts and provides a creative, useful solution to the drawbacks of conventional forecasting techniques. Ultimately, this work makes a significant contribution to the domains of data-driven decision-making, pension fund administration, and financial analytics. This research opens several avenues for extension: i) technical enhancements: incorporate deep-learning models (LSTMs) for sequence forecasting of long-term trends, ii) policy integration: align predictive outputs with compliance checks and regulatory requirements, iii) cross-sector applications: adapt the model framework to other sectors such as health insurance and social welfare, iv) resource optimization: optimize model training and inference costs for low-resource institutions using serverless computing or edge devices, and v) consider naming the modeling approach as a framework (e.g., "cloud-actuarial predictive optimization model" (CAPOM).

ACKNOWLEDGMENTS

I extend my heartfelt gratitude to my academic supervisors, whose insightful guidance, constructive critiques, and encouragement were instrumental throughout the development of this research. I am equally thankful to the faculty members of the cloud computing department at Harare Institute of Technology, whose academic support and resources provided the foundation for this work. Their dedication to fostering innovation and research excellence has been invaluable.

Special appreciation also goes to the pension fund institutions and regulatory bodies in Zimbabwe that facilitated access to vital data and domain knowledge. Their cooperation significantly enriched the practical relevance of this study. I am further indebted to my family for their unwavering support, patience, and motivation during this research journey.

FUNDING INFORMATION

Utilizing available resources, the authors advised that the research was conducted without the need for external funding, demonstrating the capacity to achieve results cost-effectively.

AUTHOR CONTRIBUTIONS STATEMENT

This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

Name of Author	C	M	So	Va	Fo	I	R	D	O	E	Vi	Su	P	Fu
Beauty Garaba	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓		✓	
Mainford Mutandavari		✓		✓	✓	✓		✓		✓	✓	✓	✓	
Jerita Chibhabha		✓		✓	✓	✓		✓		✓	✓	✓	✓	

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

The authors declare that there are no conflicts of interest related to this research.

INFORMED CONSENT

The protection of privacy is a legal right that must not be breached without individual informed consent. In cases where the identification of personal information is necessary for scientific reasons, authors should obtain full documentation of informed consent, including written permission from the patient prior to inclusion in the study. Incorporate the following (or a similar) statement: We have obtained informed consent from all individuals included in this study.

ETHICAL APPROVAL

This research utilized anonymized pension data and did not require ethical approval from the data subjects. The use of anonymized data ensured that no identifiable information was collected. This adheres to ethical guidelines for research in the pensions and insurance sector.

DATA AVAILABILITY

Due to privacy and confidentiality concerns, the data used to support the research's conclusions has been anonymized and is not available for public sharing. However, the anonymized data can be made available upon reasonable request from the author, provided that the request adheres to ethical standards and data protection laws.

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