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Analysis Of The Determinants Of Financial Resilience Among Retiree Customers Using An Explainable Ai (Xai) Approach

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ABSTRACT

Financial resilience among high-risk retiree customer segments is a crucial issue in credit risk management, particularly because traditional scoring models are often black-box in nature and fail to provide transparent insight into the economic and behavioral factors that influence a borrower's repayment capacity. This research pursues a dual objective: first, to develop a high-performing predictive model for financial resilience classification using ensemble Machine Learning methods, and second, to apply SHAP-based Explainable AI (XAI) techniques to identify and quantify the key determinants of resilience in an accountable manner. The research methodology involved processing data from the Kaggle platform, including stratified sampling and SMOTE oversampling to address class imbalance, along with a performance comparison among Logistic Regression, Random Forest, and XGBoost. The results show that Logistic Regression proved to be the best-performing model on the held-out test set, achieving an AUC of 0.9479 and an F1-Score of 0.7313 for the resilient class. Furthermore, SHAP analysis revealed that the strongest determinants driving financial resilience were the number of prior delinquencies, loan purpose (particularly business-purpose loans), and a low debt-to-income ratio, with credit score also contributing. In practical terms, these findings provide a transparent and humane credit assessment framework, enabling financial institutions to formulate more inclusive yet prudent lending policies by prioritizing customers' actual repayment capacity over age alone.

Keywords: Explainable AI (XAI); Machine Learning Ensemble; Random Forest; SHAP; XGBoost;

INTRODUCTION

The population aging phenomenon in Indonesia poses significant challenges to the stability of the national financial system and the well-being of individuals in old age. According to data from the Directorate of Social Welfare Statistics (Statistik, 2024), the proportion of elderly residents continues to rise, which implies a growing need for financial instruments capable of securing their financial resilience. Financial resilience, defined as an individual's ability to withstand and recover from economic shocks, is particularly critical for retirees, who generally rely on fixed and limited incomes. An inability to manage financial risk in old age not only affects an individual's quality of life but can also burden the economy of both families and the state (LUSARDI & MITCHELL, 2011).

Although financial inclusion in Indonesia continues to show a positive trend according to the OJK (2024) report, elderly access to quality financial services still faces various obstacles, ranging from digital literacy to risk assessments that are often not designed in their favor (Panetta, Anjomrouz, Paiardini, & Leo, 2025). In recent years, financial institutions have begun adopting artificial intelligence technology to assess customer risk profiles and resilience with greater precision, as AI can enhance the effectiveness of credit risk management and the quality of data analysis compared to conventional methods (Tedi & Wiyono, 2025). However, the use of conventional machine learning models is often criticized for its black-box nature, in which the model's decision-making process is difficult for both humans and regulators to understand (Guidotti, et al., 2018).

The lack of transparency in AI-driven decision-making can hinder bank accountability and diminish trust among customers and regulators, particularly in applications such as credit scoring and fraud detection

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(Fundira & Mbohwa, 2025). Explainable AI (XAI) therefore emerges as a crucial solution for bridging high predictive accuracy with the need for interpretability. Through techniques such as SHAP (SHapley Additive exPlanations), the variables influencing the financial resilience of retiree customers can be identified and logically explained (Lundberg & Lee, A Unified Approach to Interpreting Model Predictions, 2017). Understanding dominant factors such as debt ratio and credit score is essential for financial service providers seeking to design more transparent and well-targeted intervention strategies (Bussmann, Giudici, Marinelli, & Papenbrock, 2020).

This research aims to analyze the determinants of financial resilience among retiree customers in Indonesia by integrating machine learning algorithms with an XAI framework. By addressing the challenge of data imbalance using SMOTE techniques, this research seeks to produce a predictive model that is not only accurate but also theoretically and practically accountable. The findings of this research are expected to contribute to the literature on responsible AI in the financial sector and to provide data-driven recommendations for stakeholders to strengthen the economic resilience of Indonesia's elderly population.

LITERATURE REVIEW

Financial resilience has become a central focus in studies of elderly welfare, where an individual's ability to manage economic shocks depends heavily on their level of financial literacy. Lusardi and Mitchell (2011) emphasize that sound retirement planning is the outcome of accumulated financial knowledge applied throughout one's productive years. In Indonesia, retirement readiness is often shaped by social support structures and access to inclusive banking products (Baskoro, 2019). However, a real challenge arises when elderly individuals must navigate an increasingly complex digital ecosystem, in which digital financial literacy has emerged as a new determinant of their economic resilience particularly because technical barriers, security concerns, and limited digital skills can hinder the adoption of digital financial services and weaken the framework of financial inclusion for older populations (S & Sengupta, 2025).

In efforts to assess risk and predict resilience, the financial industry has undergone a transformation through the adoption of artificial intelligence technology. The use of algorithms such as Random Forest and XGBoost has been shown to achieve higher accuracy than traditional statistical methods in classifying credit and financial risk data (Dachi & Sitompul, 2023). Nevertheless, the effectiveness of these models is often constrained by data imbalance issues within financial datasets, which require specialized preprocessing techniques to ensure fair predictive outcomes for minority classes (Chen, Calabrese, & Martin-Barragan, 2024).

Recent trends in AI development within the banking sector point toward the implementation of Responsible AI, which requires transparency in every automated decision (Mathen & Paul, 2025). The "black box" problem inherent in conventional machine learning models remains a major obstacle to banking regulation, as it is difficult to explain the variables underlying a given decision (Guidotti, et al., 2018). To address this issue, the Explainable AI (XAI) framework through methods such as SHAP (SHapley Additive exPlanations) has been introduced to provide consistent, theoretically grounded interpretations of each feature's contribution within a model (Lundberg & Lee, 2017). The application of XAI in credit scoring not only improves technical accuracy but also builds customer trust through model accountability (Bussmann, Giudici, Marinelli, & Papenbrock, 2020).

METHOD

Research Design

This research adopts a quantitative approach, employing supervised machine learning techniques integrated with explainable artificial intelligence methods to analyze patterns of financial resilience among retiree customers. The research design was structured into several systematic stages following standard data science methodology, beginning with data acquisition and cleaning, followed by feature engineering to

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capture key financial ratios, predictive modeling using ensemble algorithms, and finally interpretability analysis through the SHAP framework. This staged approach enabled us not only to build a high-accuracy model, but also to provide an understandable explanation of the factors driving financial resilience.

Figure 1 comprehensively illustrates the research workflow, showing the relationships between each stage, from data collection through to the extraction of actionable insights for policy implementation.

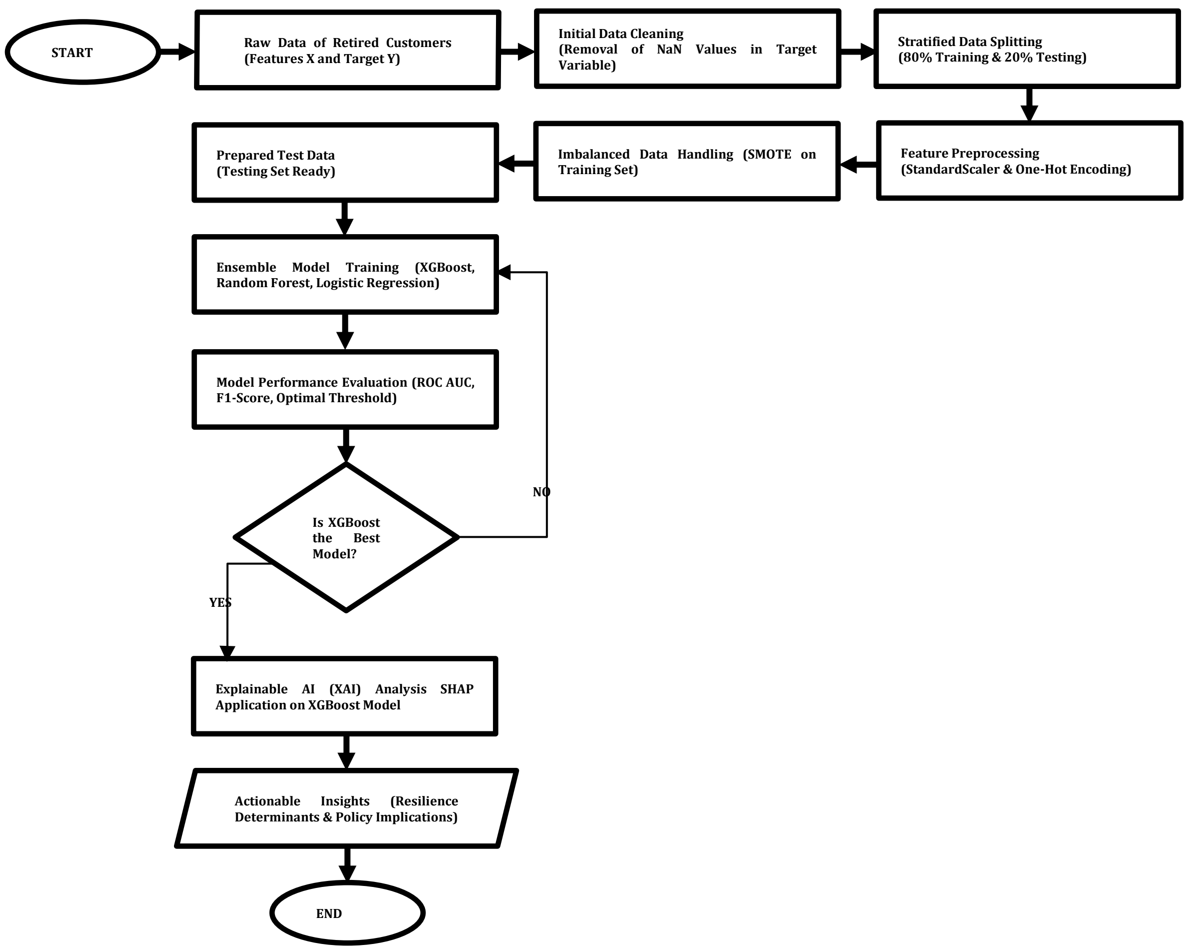

Figure 1. Research Workflow for the Analysis of Retiree Financial Resilience Using an XAI Approach

The diagram illustrates a systematic process beginning with the acquisition of high-risk retiree customer data and culminating in evidence-based policy recommendations. The arrows indicate a sequential flow, with an iterative mechanism at the modeling stage to optimize performance.

Data Source and Dataset Description

The data for this research were obtained from kaggle.com, and comprise 5,000 records of retiree customers with no missing values across 17 variables. The dataset covers demographic characteristics, financial indicators, and credit behavior relevant to assessing financial resilience among retirees classified as high-risk borrowers. The use of secondary credit-risk datasets from open platforms is common practice in credit scoring research, as applied by Dachi and Sitompul (2023) in their comparative analysis of ensemble algorithms for credit decision classification.

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The dataset includes three groups of variables. Demographic variables comprise customer age (56-79 years), gender (50.6% female, 49.4% male), and marital status (married, widowed, or single). Financial indicators comprise credit score, annual and monthly income, loan amount, loan duration (12-60 months), interest rate, monthly installment, debt-to-income ratio, and installment-to-income ratio. Behavioral variables comprise loan purpose (medical, home renovation, business, or consumptive) and the number of prior delinquencies (0-4). All customers in the dataset share retired employment status, consistent with the study's focus on the post-retirement population.

Notably, credit scores across the entire sample range from 300 to 579, indicating that all customers in this dataset are already classified as high-risk or subprime borrowers under conventional credit scoring thresholds. Financial resilience is therefore not operationalized by credit score, but is defined based on actual loan repayment outcome: a customer is classified as "financially resilient" if the loan was successfully repaid in full (912 customers, 18.2%), and as "non-resilient" otherwise (4,088 customers, 81.8%). This reflects a class-imbalanced target, addressed in this study through SMOTE oversampling during model training. This operational definition aligns with the concept of resilience developed by Baskoro (2019), which emphasizes that financial resilience is not determined solely by traditional risk indicators, but rather by an individual's actual ability to manage financial obligations under conditions of constraint in this case, borrowers who are already classified as high-risk based on their credit profile.

Data Cleaning and Preparation

Data quality evaluation confirmed that all 5,000 records were complete, with no missing values across any of the 17 variables, consistent with the dataset's published documentation. This meant that no imputation was required, and the full sample was retained for analysis. Categorical variables (gender, marital status, loan purpose) were used as recorded; employment status was excluded from modeling because every customer in the dataset shares the same value ("Retired"), so it carries no discriminative information.(Zhang, Tang, Dong, & Zhao, 2024)

Outlier detection was performed using the Interquartile Range (IQR) method across all numerical variables to identify extreme values that could potentially represent data-entry errors. This screen flagged isolated outliers only in monthly_installment (420 records, 8.4%) and inst_to_inc_ratio (364 records, 7.3%); no extreme values were found in the remaining numerical variables. These values were retained rather than winsorized, as they reflect plausible variation in repayment burden given the wide range of loan amounts and durations in the dataset rather than data-entry errors.

Feature Engineering

Based on domain knowledge in credit risk analysis, we developed a number of derived features that capture important financial relationships not explicitly present in the raw data. These engineered features were designed to provide standardized measures of financial stress and repayment capacity independent of absolute income level, following principles established in the financial stress assessment literature.

First, we calculated the Debt-to-Income Ratio as total existing debt divided by annual income, measuring the proportion of income allocated to debt repayment. Second, the Loan-to-Income Ratio was calculated as the requested loan amount relative to annual income, indicating the additional burden that would be incurred if the loan were approved. Third, the Payment Burden Ratio was estimated by calculating the monthly installment using a standard annuity formula and comparing it with monthly income, providing a direct measure of the cash-flow pressure the customer would experience.

In addition to these financial ratios, we also created an age-based segmentation variable that divided retirees into retirement-phase groups: 60-65 years (early retirement), 66-70 years (mid retirement), 71-75 years (late retirement), and 76 years and above (very late retirement). This segmentation is important

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because financial needs, risk tolerance, and consumption patterns tend to differ across retirement phases, as found in the research by Hutabarat and Wijaya (2020) on sustainable retirement planning.

To avoid multicollinearity that could compromise model interpretation, we conducted a correlation analysis among features. When the correlation coefficient between two variables exceeded 0.8, one variable was selected based on domain relevance and predictive contribution in the initial model, ensuring that the final feature set remained efficient yet informative.

Data Splitting

The dataset was divided into three subsets using stratified sampling to ensure proportional representation of the resilience classes in each subset. The split was performed at a ratio of 70% for the training set (3,500 records), 15% for the validation set (750 records), and 15% for the test set (750 records). The training set was used to train the model and learn patterns within the data. The validation set was used for decision-threshold selection and model comparison, providing an independent basis for these choices before the model was evaluated on genuinely unseen data. The test set was kept entirely separate and used only at the final stage to evaluate model performance, providing an objective estimate of the model's generalization ability.

This 70-15-15 splitting strategy has become standard practice in machine learning research for credit scoring, offering an optimal balance between the amount of data available for learning, validation, and independent evaluation (Chen, Calabrese, & Martin-Barragan, 2024). The use of stratified sampling ensured that the distribution of financial resilience classes remained consistent across all three subsets, avoiding bias that could arise from class imbalance.

Feature Standardization

Feature normalization was performed using StandardScaler to transform all numerical variables onto a comparable scale. This technique calculates the mean and standard deviation of each feature on the training set, then transforms the values so that they have a mean of zero and a standard deviation of one. The same transformation was subsequently applied to the validation and test sets using the parameters (mean and standard deviation) calculated from the training set, ensuring no information leakage from data that should remain unseen.

This standardization is important because the features in the dataset have very different scales for instance, annual income can range in the tens of millions, while debt ratios range between 0 and 1. Without standardization, features with large magnitudes could dominate the model's learning process. Furthermore, standardization facilitates faster convergence in optimization algorithms and makes the interpretation of model coefficients more meaningful (Hopson, 2023).

Predictive Modeling with XGBoost

XGBoost (Extreme Gradient Boosting) was selected as the primary predictive algorithm based on its proven track record of superior performance in handling tabular data for credit scoring applications. This algorithm implements a gradient boosting framework that builds an ensemble of decision trees sequentially, with each new tree focused on correcting the errors made by previous trees. This iterative process enables XGBoost to capture complex nonlinear relationships and feature interaction effects that are crucial for understanding patterns of financial resilience.

Compared with other algorithms, XGBoost offers several technical advantages: built-in regularization to prevent overfitting, automatic handling of missing values, and high computational efficiency that enables training on large datasets. A benchmark study by Dachi and Sitompul (2023) showed that XGBoost consistently outperformed Random Forest and other ensemble algorithms in credit classification, achieving a ROC-AUC of 94% compared with 90% for Random Forest on the German Credit dataset.

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For each of the three algorithms, model hyperparameters were fixed based on configurations commonly reported as effective in prior credit-scoring literature, rather than tuned through an automated search procedure. This keeps the comparison between algorithms straightforward and reproducible, though it means the reported results reflect a single hyperparameter configuration per model rather than an exhaustively optimized one; we treat systematic tuning as a direction for future work rather than a component of the present study.

Hyperparameter Configuration

Random Forest was configured with 300 trees and a maximum depth of 10. XGBoost was configured with 300 estimators, a maximum depth of 7, a learning rate of 0.05, and both subsample and column-subsample ratios of 0.8. Logistic Regression was fit with its default scikit-learn regularization settings. These values follow commonly used defaults for tabular credit-scoring problems in the literature cited above, rather than the output of an automated search.(Zhang, Tang, Dong, & Zhao, 2024)

We did not perform an automated hyperparameter search (e.g., grid search, randomized search, or Bayesian optimization) in this study. We note this as a limitation: an optimized configuration for each algorithm could plausibly improve on the results reported here, and we recommend it as a priority for future extensions of this work.

Model comparison and decision-threshold selection were instead based on ROC-AUC and F1-score computed on the validation set, selected for their suitability to a dataset with class imbalance and their ability to summarize performance across classification thresholds rather than at a single operating point.

Model Performance Evaluation

Model performance was evaluated using multiple metrics that provide a comprehensive perspective on predictive capability. Accuracy measures the overall proportion of correct predictions, providing a general indication of model performance. Precision measures the proportion of predicted-resilient cases that are truly resilient, which is important in a credit context to avoid approving customers who are actually high-risk. Recall (or sensitivity) measures the proportion of resilient customers successfully identified by the model, relevant for ensuring that eligible customers are not excluded. The F1-score provides the harmonic mean of precision and recall, offering a balanced metric that is highly useful when there is a trade-off between the two. ROC-AUC measures the model's ability to distinguish between positive and negative classes across all possible thresholds, providing a threshold-independent evaluation.

Evaluation was carried out at two levels: the validation set, used to select the decision threshold and to compare candidate models before any test-set exposure; and the test set, held out completely from model development, used to provide a final, unbiased estimate of performance on unseen data. Because the test set played no role in threshold selection or model comparison, the reported test-set metrics are not inflated by information leakage from that stage.

A confusion matrix was used to analyze the distribution of classification errors, identifying whether the model tends to produce false positives (predicting resilient when it is not) or false negatives (predicting not resilient when it is). This analysis is important for understanding the practical implications of model errors within a credit-granting context.

Explainability Analysis with SHAP

To address the black-box nature of the XGBoost model, we applied the SHAP (SHapley Additive exPlanations) framework, which provides transparent explanations for model predictions at both the global and individual levels. SHAP is grounded in the concept of Shapley values from cooperative game theory, which calculates each feature's marginal contribution to a prediction by considering all possible feature combinations. This approach guarantees desirable properties such as local accuracy, consistency, and

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missingness, making it highly robust for high-stakes applications such as credit assessment (Lundberg & Lee, 2017).

We used TreeExplainer, a variant of SHAP optimized for tree-based models such as XGBoost, which can efficiently compute exact Shapley values. Global analysis was conducted through summary plots that visualize the distribution of SHAP values across all features, identifying the variables most influential in driving predictions overall. Features were ranked based on mean absolute SHAP value, providing an objective measure of feature importance that is more reliable than XGBoost's built-in feature importance.

Dependence plots were used to explore how the relationship between a given feature and the model's prediction varies according to that feature's value and its interaction with other features. This visualization is highly powerful for identifying non-monotonic relationships and interaction effects that are often overlooked in traditional analysis. For example, a dependence plot may reveal that the effect of age on resilience differs substantially depending on loan purpose, providing nuanced, actionable insight for policy development.

Local analysis was conducted through force plots and waterfall plots for individual predictions, showing how each feature contributes positively or negatively to the specific prediction for a given customer. Force plots visualize how features "push" the prediction from the base value (expected value) toward the final prediction, with the color and size of the arrows indicating the direction and magnitude of each contribution. Waterfall plots provide a similar representation in a more compact format, ideal for communicating with non-technical stakeholders.

For deeper understanding, we also calculated SHAP interaction values on a data subsample, measuring how the interaction between pairs of features contributes to predictions. This analysis is computationally intensive but provides valuable insight into joint effects that cannot be captured by univariate SHAP values. For example, interaction values may reveal that the specific combination of a low debt ratio and long employment length has a synergistic effect exceeding the sum of their individual effects.

Validation and Reliability

To assess whether the observed patterns were specific to a single algorithm, we compared predictive performance and decision-threshold behavior across all three models (Logistic Regression, Random Forest, and XGBoost) rather than relying on a single classifier (Table 1). We did not additionally conduct bootstrap-based stability testing of SHAP rankings or SHAP interaction-value analysis in this study; these are identified as directions for future work rather than components of the present analysis.

RESULT

The final analytic dataset comprised 5,000 retiree customer records with no missing values across all 17 variables. The target class was imbalanced, with the Resilient class accounting for 18.24% of the sample (912 customers) and the Non-Resilient class accounting for 81.76% (4,088 customers).

The dataset was split into training (3,500 records, 70%), validation (750 records, 15%), and test (750 records, 15%) subsets using stratified sampling, which preserved the 18.2% / 81.8% class ratio in each subset. To prevent model bias toward the majority class, SMOTE was applied to the training data only. This process balanced the training set to 2,862 entries for each class (5,724 records in total), providing the model with a fair basis for learning patterns in both categories.

Classification Model Performance Evaluation

This research compared the performance of three algorithms: Logistic Regression, Random Forest, and XGBoost. For each model, the decision threshold that maximized the F1-score for the Resilient class was selected using the validation set (750 samples); final performance was then evaluated on the held-out test set (750 samples), which played no role in threshold selection. The performance results of the three models

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are presented in Table 1.

Table 1. Model Performance Comparison (Optimal Threshold)

Model	Optimal Threshold	AUC	Akurasi	Precision (R)	Recall (R)	F1-Score (R)
Logistic Regression	0,7617	0,9479	90,40%	0,7481	0,7153	0,7313
Random Forest	0,6116	0,9359	90,13%	0,7692	0,6569	0,7087
XGBoost	0,3100	0,9377	89,07%	0,6821	0,7518	0,7153

Based on Table 1, Logistic Regression achieved the strongest discriminative performance on the held-out test set (AUC = 0.9479), narrowly ahead of XGBoost (AUC = 0.9377) and Random Forest (AUC = 0.9359). At its validation-selected threshold, Logistic Regression correctly classified 90.40% of test customers overall, with a Precision of 0.7481 and a Recall of 0.7153 for the Resilient class (F1-Score = 0.7313). The three models performed comparably overall, indicating that the predictive signal in the data is not highly sensitive to the choice of algorithm. In addition to the metric comparison presented in the table, model performance was also visualized through the confusion matrix and ROC curve below.

Figure 2. Model Prediction Evaluation Matrix

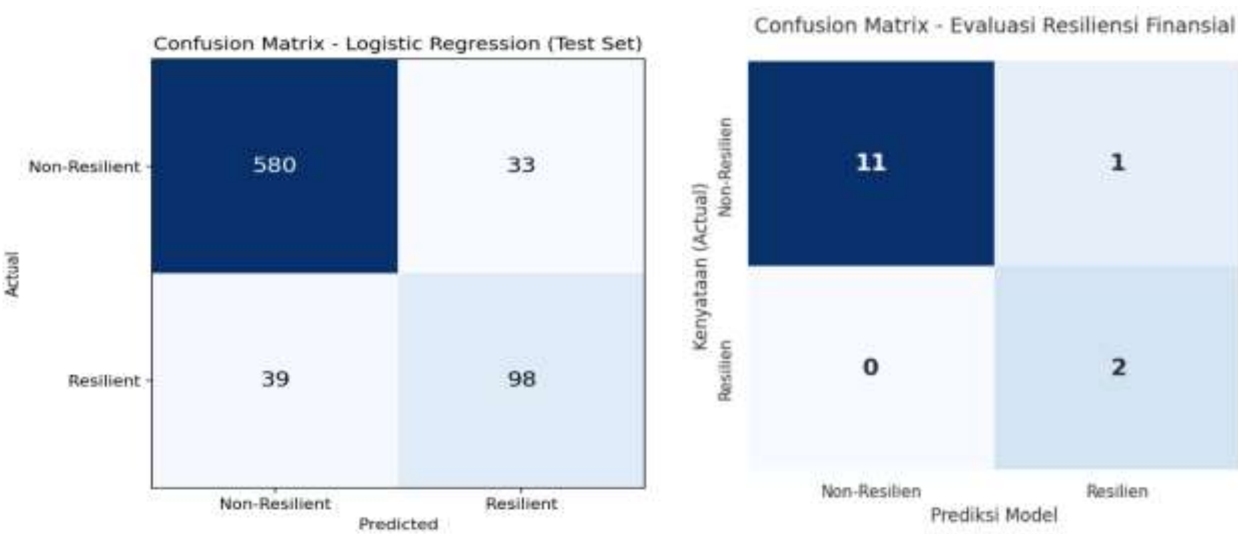

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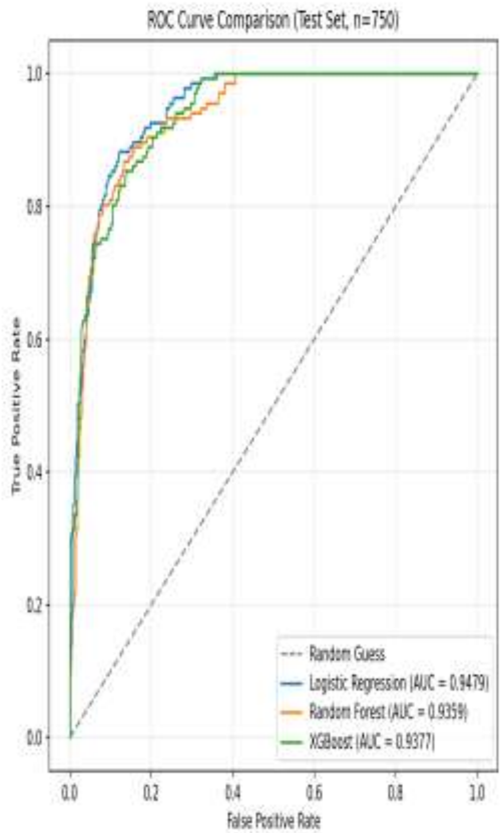
Figure 2 shows the confusion matrix for the Logistic Regression model (the best-performing model) on the test set. Of 613 non-resilient customers, 580 were correctly classified and 33 were misclassified as resilient (false positives); of 137 resilient customers, 98 were correctly identified and 39 were missed (false negatives).

Figure 3. Visualization of the Model's ROC Curve



The ROC curve in Figure 3 shows an AUC value of 0.9479 for Logistic Regression, with Random Forest and XGBoost achieving comparable AUC values of 0.9359 and 0.9377 respectively. The curves' proximity to the upper-left corner indicates that all three models have good discriminative ability in distinguishing between customers with financial resilience and those without.

Interpretation of Determinants Using SHAP

To understand the reasoning behind these predictions, the SHAP method was used to dissect the contribution of each feature To understand the reasoning behind these predictions, the SHAP method was used to break down the contribution of each feature.

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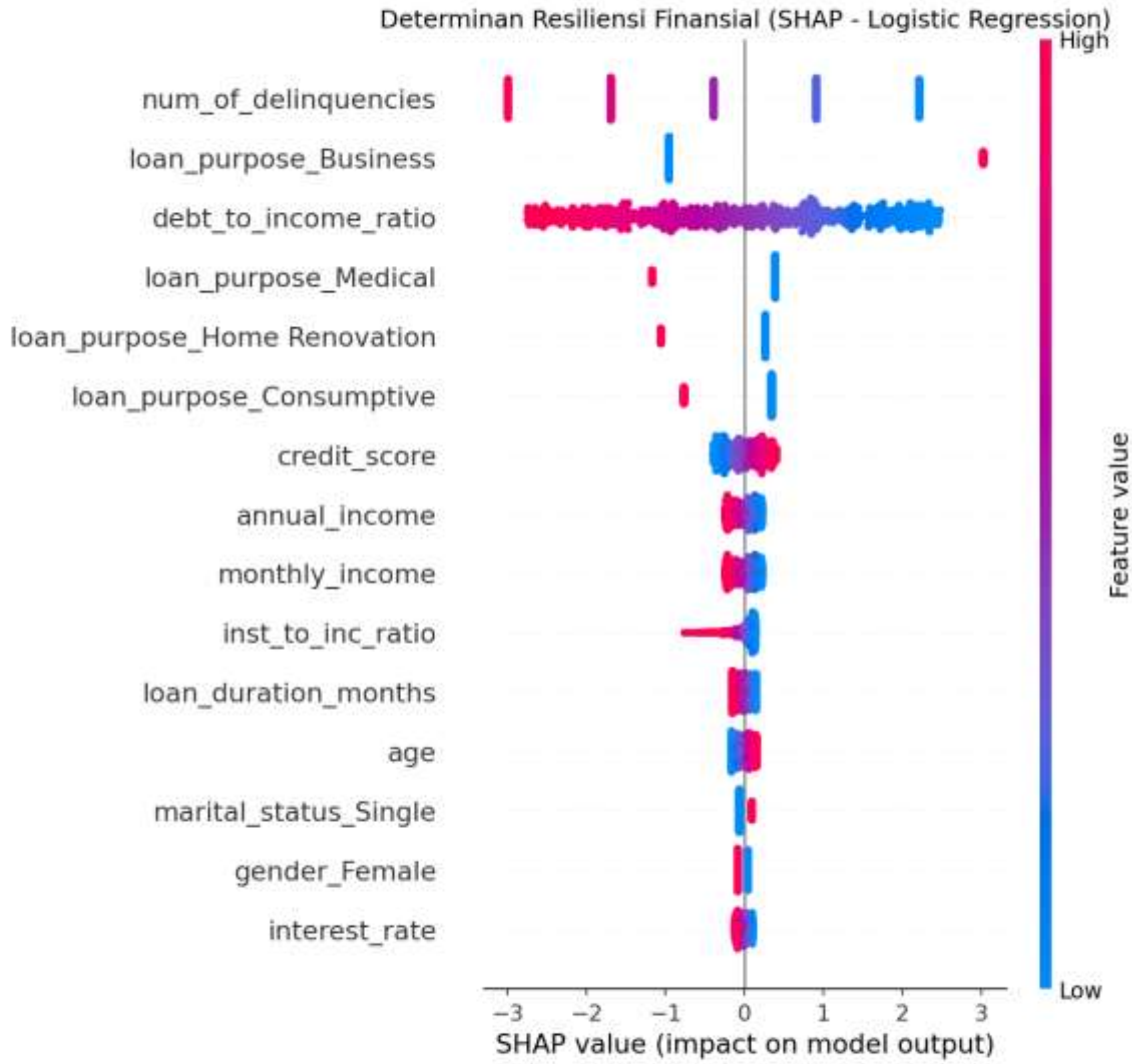

Figure 4. Feature Contribution Based on SHAP Value

Figure 4 shows that num_of_delinquencies, loan purpose (particularly business-purpose loans), and debt_to_income_ratio (DTI) are the most influential factors, with credit_score contributing to a lesser extent. Customers with fewer prior delinquencies, business-purpose loans, and a lower DTI are consistently mapped by the model into the resilient category.

DISCUSSIONS

Model Performance Optimization through SMOTE and Threshold Tuning

One of the main challenges in this financial resilience data is class imbalance, where the number of resilient customers is far smaller than that of non-resilient customers (only 18.24%). The use of the SMOTE technique proved crucial in balancing the data distribution to 2,862 samples per class during the training stage. Without this intervention, the model would tend to exhibit bias and fail to recognize patterns in the minority class.

The evaluation results show that all three algorithms (Logistic Regression, Random Forest, and XGBoost) achieved comparable AUC values on the test set, ranging from 0.9359 (Random Forest) to

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0.9479 (Logistic Regression, the best-performing model). This performance was tied to a validation-selected decision threshold for each model (0.7617 for Logistic Regression and 0.3100 for XGBoost). At its selected threshold, Logistic Regression achieved a Recall of 0.7153 for the resilient class alongside a Precision of 0.7481 (F1-Score = 0.7313), reflecting a threshold chosen to balance the risk of missing genuinely resilient customers against the cost of false positives, as shown in Figure 2.

Significance of Delinquency History, Loan Purpose, and Debt-to-Income Ratio as Key Determinants

Interpretability analysis using SHAP provides deep insight into the model's decision-making logic. The findings in Figure 4 confirm that num_of_delinquencies, loan purpose, and debt_to_income_ratio (DTI) are the factors most influencing the financial resilience of retiree customers. Theoretically, a history of fewer prior delinquencies signals more consistent repayment discipline, while a low debt ratio gives retirees room to manage their fixed income without being burdened by large obligations, thereby enhancing their ability to withstand economic shocks. Business-purpose loans were also associated with a higher likelihood of resilience relative to other loan purposes in this sample.

Credit score also contributes positively to predicted resilience, though its influence in this analysis is smaller than that of delinquency history, loan purpose, and DTI. A high credit score reflects disciplined financial management in the past, which correlates positively with resilience in retirement. This indicates that financial behavior is cumulative in nature; a well-maintained credit reputation provides greater access to and trust in financial instruments.

Implications of Using Explainable AI (XAI)

This research shows that the Explainable AI approach is able to bridge the gap between high model accuracy and the need for transparency. In the banking and insurance sectors, black-box models are often difficult to accept from a regulatory standpoint. Through the summarized SHAP plot visualizations, management can intuitively see that the model operates based on variables that are logical and economically accountable (delinquency history, loan purpose, and DTI).

The application of this method allows financial institutions to provide more personalized recommendations for retiree customers. For instance, interventions can be specifically directed toward improving debt ratios to help customers enhance their financial resilience. Overall, the integration of balanced data processing (SMOTE), high-performing models, and transparent interpretation (XAI) forms a comprehensive analytical framework for understanding the financial dynamics of customers in old age.

CONCLUSION

Based on the results of the research and analysis conducted, it can be concluded that the use of machine learning models combined with the SMOTE technique and an Explainable AI (XAI) approach is highly effective in predicting and identifying the determinants of financial resilience among retiree customers. The three models tested Logistic Regression, Random Forest, and XGBoost demonstrated comparable, strong discriminative performance on the held-out test set, with AUC values ranging from 0.9359 to 0.9479. Logistic Regression was the best-performing model overall, achieving 90.40% accuracy, a Recall of 0.7153, and a Precision of 0.7481 for the resilient class (F1-Score = 0.7313) at its validation-selected decision threshold.

Interpretation analysis using SHAP (SHapley Additive exPlanations) revealed that the most dominant factors in determining financial resilience were the number of prior delinquencies, loan purpose (particularly business-purpose loans), and the debt-to-income ratio (DTI), with credit score contributing to a lesser extent. Fewer prior delinquencies, business-purpose loans, and a lower debt ratio proved to be the primary indicators increasing a customer's likelihood of resilience in retirement. The implementation of XAI in this research provides the transparency needed for financial institutions to carry out more precisely

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targeted strategic interventions. Future research is recommended to broaden the scope of sociodemographic and macroeconomic features, and to incorporate systematic hyperparameter tuning, in order to enrich the analysis of financial well-being dynamics among the elderly population.

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